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Resiliency and Well-Being: Trajectories of Change over Time

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Graduate Program in Psychology

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ABSTRACT

Resiliency is often considered an attribute that can assist an individual in overcoming adversity. The predominant theme in the literature is that resiliency is positively related to achieving positive outcomes after a challenging experience. For example, stemming from Luthans and colleagues’ work on Psychological Capital (Luthans, Youssef, & Avolio, 2007), resiliency has been positively linked to psychological well-being, job satisfaction, and job performance. However, scant research is available on the processes behind resiliency and the mechanisms that promote well-being in the face of adversity. Therefore, the two studies comprising this dissertation aimed to address focal research questions around a) why is resiliency necessary? and b) how does resiliency progress over time?

Study 1 drew upon and integrated Self-Determination Theory (SDT; Deci & Ryan, 1985) into the resiliency process to offer an understanding of why resiliency may be necessary. It was proposed that individuals that have faced an adverse event would experience a substantial decrease in the satisfaction of the basic psychological needs comprising SDT. Moreover, only those individuals that experienced a decrease in SDT need satisfaction would demonstrate the need for resiliency. Using latent transition analysis, Study 1 demonstrated that only those individuals who experienced a substantial decrease in SDT need satisfaction demonstrated a relation with resiliency. Whereas consistent levels of SDT need satisfaction over time were not related to resiliency.

Study 2 focused on exploring the trajectory of resiliency, as it unfolded over time in response to the common, yet adverse, workplace experience of being fired. Study 2 revealed a non-linear trajectory characterized by decreasing resiliency levels between the first and second assessments, and then increasing levels between the second and third assessments. Results also suggested that the resiliency components could help account for significant
proportions of variance in the two important outcomes examined: psychological well-being and job search self-efficacy.

Together, the findings from Studies 1 and 2 provided additional evidence of validity for the King and Rothstein (2010) model of resiliency, and its associated measure, the Workplace Resiliency Inventory (McLarnon & Rothstein, 2013). Additional implications for practice and directions for future research are also discussed.

Keywords: resiliency (psychological); well-being; self-determination theory; longitudinal theory; unemployment; latent profile analysis; latent difference scores
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I would also like to thank my committee members, Drs. Richard Goffin, John Meyer, Paul Tremblay, Lyn Purdy, and Greg Irving. This project has been improved as a result of their thoughtful insights, suggestions, and feedback. As well, this dissertation would not have been possible without the generous financial support from the Social Sciences and Humanities Research Council of Canada. I would also like to express my gratitude towards Dr. Thomas O’Neill for his mentorship.

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To Rima: without your patience, support, and understanding none of this, nor our many adventures together over the last few years, would have been possible. Thank you. Here’s to many more years of adventures -- wherever life takes us.

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# TABLE OF CONTENTS

Abstract .............................................................................................................................. ii  
Acknowledgements ........................................................................................................ iv  
Table of Contents ........................................................................................................... v  
List of Tables .................................................................................................................. viii  
List of Figures ............................................................................................................... ix  
List of Appendices ......................................................................................................... x  
List of Abbreviations ..................................................................................................... xi  
Introduction ................................................................................................................... 1  
  Resiliency in the Organizational Literature ................................................................. 3  
  PsyCap Research Evidence ......................................................................................... 6  
  PsyCap over Time ........................................................................................................ 9  
  The General State-like Nature of Resiliency .............................................................. 12  
  Shortcomings of the PsyCap Model and its Resilience Facet ................................... 15  
  The King and Rothstein (2010) Model ....................................................................... 17  
  Measurement of King and Rothstein’s (2010) Model of Resiliency ......................... 22  
  Current Studies .......................................................................................................... 23  
Study 1 ............................................................................................................................. 25  
  Need Satisfaction and Resiliency ............................................................................... 25  
  Self-Determination Theory (SDT) Background ....................................................... 25  
  Summary and Integration ............................................................................................ 30  
  Recent Self-Determination Theory Research ........................................................... 31  
    Person-centered Approaches .................................................................................. 31  
    Person-centered Approaches and SDT ................................................................. 35  
  SDT Need Satisfaction During Challenging Life Transitions .................................... 38  
Method ............................................................................................................................. 40  
  Participants ................................................................................................................... 40  
  Measures ..................................................................................................................... 41  
  Procedure .................................................................................................................... 43  
  Analytical Procedure ................................................................................................. 44  
    Latent Transition Analysis ....................................................................................... 44
<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Testing Drop-out Effects</td>
<td>121</td>
</tr>
<tr>
<td>Results</td>
<td>123</td>
</tr>
<tr>
<td>Longitudinal Confirmatory Factor Analyses</td>
<td>123</td>
</tr>
<tr>
<td>Latent Difference Scores</td>
<td>128</td>
</tr>
<tr>
<td>Power Analyses</td>
<td>132</td>
</tr>
<tr>
<td>Hierarchical Multiple Regressions</td>
<td>135</td>
</tr>
<tr>
<td>Power Analyses</td>
<td>149</td>
</tr>
<tr>
<td>Sensitivity Analyses</td>
<td>150</td>
</tr>
<tr>
<td>Discussion</td>
<td>154</td>
</tr>
<tr>
<td>Latent Difference Scores</td>
<td>128</td>
</tr>
<tr>
<td>Power Analyses</td>
<td>132</td>
</tr>
<tr>
<td>Hierarchical Multiple Regressions</td>
<td>135</td>
</tr>
<tr>
<td>Power Analyses</td>
<td>149</td>
</tr>
<tr>
<td>Sensitivity Analyses</td>
<td>150</td>
</tr>
<tr>
<td><strong>Discussion</strong></td>
<td>154</td>
</tr>
<tr>
<td><strong>Longitudinal Validity</strong></td>
<td>155</td>
</tr>
<tr>
<td><strong>Trajectories of Change</strong></td>
<td>157</td>
</tr>
<tr>
<td>Associations Between Change in Resiliency and Change in Psychological Well-Being</td>
<td>161</td>
</tr>
<tr>
<td>Associations Between Change in Resiliency and Change in Job Search Self-Efficacy</td>
<td>168</td>
</tr>
<tr>
<td>Summary of Findings</td>
<td>171</td>
</tr>
<tr>
<td>Limitations</td>
<td>172</td>
</tr>
<tr>
<td>Conclusion</td>
<td>177</td>
</tr>
<tr>
<td><strong>General Discussion</strong></td>
<td>178</td>
</tr>
<tr>
<td>Ployhart and Vandenberg’s (2010) Requirements</td>
<td>178</td>
</tr>
<tr>
<td>The Why and How of Resiliency</td>
<td>179</td>
</tr>
<tr>
<td>Theoretical Contribution</td>
<td>180</td>
</tr>
<tr>
<td>Complementary Relations with PsyCap</td>
<td>183</td>
</tr>
<tr>
<td>Longitudinal Validity</td>
<td>185</td>
</tr>
<tr>
<td>Implications</td>
<td>186</td>
</tr>
<tr>
<td>Conclusion</td>
<td>191</td>
</tr>
<tr>
<td><strong>References</strong></td>
<td>193</td>
</tr>
<tr>
<td>Appendices</td>
<td>240</td>
</tr>
<tr>
<td>Curriculum Vita</td>
<td>351</td>
</tr>
</tbody>
</table>
## LIST OF TABLES

<table>
<thead>
<tr>
<th>Table</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Workplace Resiliency Inventory Scale Content</td>
<td>24</td>
</tr>
<tr>
<td>2</td>
<td>Study 1 Time 1 and Time 2 Intercorrelation Matrix</td>
<td>56</td>
</tr>
<tr>
<td>3</td>
<td>Study 1 Reliability Estimates</td>
<td>57</td>
</tr>
<tr>
<td>4</td>
<td>Study 1 LPA Model Fit Indices for Time 1</td>
<td>59</td>
</tr>
<tr>
<td>5</td>
<td>Study 1 LPA Membership Proportions for Time 1</td>
<td>61</td>
</tr>
<tr>
<td>6</td>
<td>Study 1 LPA Means for Time 1</td>
<td>64</td>
</tr>
<tr>
<td>7</td>
<td>Study 1 PWB and Resiliency Means for Time 1 LPA</td>
<td>67</td>
</tr>
<tr>
<td>8</td>
<td>Study 1 LPA Model Fit Indices for Time 2</td>
<td>68</td>
</tr>
<tr>
<td>9</td>
<td>Study 1 LPA Membership Proportions for Time 2</td>
<td>69</td>
</tr>
<tr>
<td>10</td>
<td>Study 1 LPA Means for Time 2</td>
<td>72</td>
</tr>
<tr>
<td>11</td>
<td>Study 1 PWB and Resiliency Means for Time 2 LPA</td>
<td>75</td>
</tr>
<tr>
<td>12</td>
<td>Study 1 Cross-sectional Transition Probabilities</td>
<td>78</td>
</tr>
<tr>
<td>13</td>
<td>Study 1 Latent Difference Score Model Fit Indices</td>
<td>83</td>
</tr>
<tr>
<td>14</td>
<td>Study 1 Mover-Stayer Latent Difference Scores Means</td>
<td>84</td>
</tr>
<tr>
<td>15</td>
<td>Study 2 Participants</td>
<td>114</td>
</tr>
<tr>
<td>16</td>
<td>Study 2 Reliability Estimates</td>
<td>117</td>
</tr>
<tr>
<td>17</td>
<td>Study 2 Time 1 Intercorrelation Matrix</td>
<td>124</td>
</tr>
<tr>
<td>18</td>
<td>Study 2 Time 2 Intercorrelation Matrix</td>
<td>125</td>
</tr>
<tr>
<td>19</td>
<td>Study 2 Time 3 Intercorrelation Matrix</td>
<td>126</td>
</tr>
<tr>
<td>20</td>
<td>Study 2 Time 1 → Time 2 Latent Difference Score Model Fit Summaries</td>
<td>131</td>
</tr>
<tr>
<td>21</td>
<td>Study 2 Time 2 → Time 3 Latent Difference Score Model Fit Summaries</td>
<td>133</td>
</tr>
<tr>
<td>22</td>
<td>Study 2 Hierarchical Multiple Regression Results for Time 1 → Time 2 PWB on Time 1 → Time 2 WRI and PsyCap Predictors</td>
<td>138</td>
</tr>
<tr>
<td>23</td>
<td>Study 2 Hierarchical Multiple Regression Results for Time 2 → Time 3 PWB on Time 1 → Time 3 WRI and PsyCap Predictors</td>
<td>141</td>
</tr>
<tr>
<td>24</td>
<td>Study 2 Hierarchical Multiple Regression Results for Time 2 → Time 3 PWB on Time 2 → Time 3 WRI and PsyCap Predictors</td>
<td>143</td>
</tr>
<tr>
<td>25</td>
<td>Study 2 Hierarchical Multiple Regression Results for Time 1 → Time 2 JSSE on Time 1 → Time 2 WRI and PsyCap Predictors</td>
<td>145</td>
</tr>
<tr>
<td>26</td>
<td>Study 2 Hierarchical Multiple Regression Results for Time 2 → Time 3 JSSE on Time 1 → Time 2 WRI and PsyCap Predictors</td>
<td>147</td>
</tr>
<tr>
<td>27</td>
<td>Study 2 Hierarchical Multiple Regression Results for Time 2 → Time 3 JSSE on Time 2 → Time 3 WRI and PsyCap Predictors</td>
<td>148</td>
</tr>
</tbody>
</table>
## LIST OF FIGURES

<table>
<thead>
<tr>
<th>Figure</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>King and Rothstein (2010) Model of Resiliency</td>
<td>21</td>
</tr>
<tr>
<td>2</td>
<td>Elbow Plot of Time 1 LPA Information Criteria</td>
<td>62</td>
</tr>
<tr>
<td>3</td>
<td>Self-Determination Theory Means from Time 1 LPA</td>
<td>65</td>
</tr>
<tr>
<td>4</td>
<td>Elbow Plot of Time 2 LPA Information Criteria</td>
<td>71</td>
</tr>
<tr>
<td>5</td>
<td>Self-Determination Theory Mean from Time 2 LPA</td>
<td>73</td>
</tr>
<tr>
<td>6</td>
<td>Study 2 Observed Scores</td>
<td>130</td>
</tr>
</tbody>
</table>
LIST OF APPENDICES

<table>
<thead>
<tr>
<th>Appendix</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Latent Profile Analysis Fit Indices</td>
<td>240</td>
</tr>
<tr>
<td>B</td>
<td>Pilot Study</td>
<td>242</td>
</tr>
<tr>
<td>C</td>
<td>Study 1 Ethics Approval</td>
<td>268</td>
</tr>
<tr>
<td>D</td>
<td>Self-Determination Theory items</td>
<td>269</td>
</tr>
<tr>
<td>E</td>
<td>Psychological Well-being items</td>
<td>270</td>
</tr>
<tr>
<td>F</td>
<td>Psychological Capital (PsyCap) items</td>
<td>271</td>
</tr>
<tr>
<td>G</td>
<td>Workplace Resiliency Inventory (WRI) items</td>
<td>272</td>
</tr>
<tr>
<td>H</td>
<td>Study 1 Priming Scenario</td>
<td>274</td>
</tr>
<tr>
<td>I</td>
<td>Latent Profile Analysis Invariance Steps</td>
<td>275</td>
</tr>
<tr>
<td>J</td>
<td>Study 1 Drop-out Effects</td>
<td>280</td>
</tr>
<tr>
<td>K</td>
<td>Study 1 Measurement Invariance Results</td>
<td>284</td>
</tr>
<tr>
<td>L</td>
<td>LPA Invariance Results</td>
<td>295</td>
</tr>
<tr>
<td>M</td>
<td>Latent Transition Analysis Specifications</td>
<td>298</td>
</tr>
<tr>
<td>N</td>
<td>Mover-Stayer Differences</td>
<td>300</td>
</tr>
<tr>
<td>O</td>
<td>Correlations Between Change in Psychological Well-Being and Resiliency Variables in Mover-Stayer Model</td>
<td>301</td>
</tr>
<tr>
<td>P</td>
<td>Study 2 Ethics Approval</td>
<td>302</td>
</tr>
<tr>
<td>Q</td>
<td>Study 2 Priming Scenario</td>
<td>303</td>
</tr>
<tr>
<td>R</td>
<td>Job Search Self-Efficacy items</td>
<td>304</td>
</tr>
<tr>
<td>S</td>
<td>Study 2 Sensitivity Analyses, Measurement Invariance</td>
<td>305</td>
</tr>
<tr>
<td>T</td>
<td>Study 2 Sensitivity Analyses, Hierarchical Multiple Regression</td>
<td>316</td>
</tr>
<tr>
<td>U</td>
<td>Study 2 Drop-out Effects</td>
<td>322</td>
</tr>
<tr>
<td>V</td>
<td>Study 2 Measurement Invariance Results</td>
<td>326</td>
</tr>
<tr>
<td>W</td>
<td>Study 2 Latent Difference Score Power Analyses, Satorra and Saris Method</td>
<td>344</td>
</tr>
<tr>
<td>X</td>
<td>Study 2 Latent Difference Score Power Analyses, Monte Carlo Method</td>
<td>345</td>
</tr>
<tr>
<td>Y</td>
<td>Study 2 Latent Difference Score Hierarchical Multiple Regression Power Analyses</td>
<td>349</td>
</tr>
<tr>
<td>Z</td>
<td>Correlations Between Scores Exported From Invariant LCFAs Across Study 1 and Study 2 Samples</td>
<td>350</td>
</tr>
</tbody>
</table>
# LIST OF ABBREVIATIONS

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>aBIC</td>
<td>Sample-size adjusted BIC</td>
</tr>
<tr>
<td>AIC</td>
<td>Akaike Information Criterion</td>
</tr>
<tr>
<td>aLMR</td>
<td>Adjusted Lo-Mendell-Rubin test</td>
</tr>
<tr>
<td>ANOVA</td>
<td>Analysis of variance</td>
</tr>
<tr>
<td>BIC</td>
<td>Bayesian Information Criterion</td>
</tr>
<tr>
<td>BLRT</td>
<td>Bootstrapped likelihood ratio test</td>
</tr>
<tr>
<td>CAIC</td>
<td>Consistent Akaike Information Criterion</td>
</tr>
<tr>
<td>CFA</td>
<td>Confirmatory factor analysis</td>
</tr>
<tr>
<td>CFI</td>
<td>Comparative fit index</td>
</tr>
<tr>
<td>COR</td>
<td>Conservation of resources</td>
</tr>
<tr>
<td>FIML</td>
<td>Full information maximum likelihood</td>
</tr>
<tr>
<td>IR</td>
<td>Initial Responses, a facet scale of the WRI</td>
</tr>
<tr>
<td>JSSE</td>
<td>Job search self-efficacy</td>
</tr>
<tr>
<td>LCA</td>
<td>Latent class analysis</td>
</tr>
<tr>
<td>LCFA</td>
<td>Longitudinal confirmatory factor analysis</td>
</tr>
<tr>
<td>LDS</td>
<td>Latent difference score</td>
</tr>
<tr>
<td>LGM</td>
<td>Latent growth model</td>
</tr>
<tr>
<td>LPA</td>
<td>Latent profile analysis</td>
</tr>
<tr>
<td>LRT</td>
<td>Likelihood ratio test</td>
</tr>
<tr>
<td>LTA</td>
<td>Latent transition analysis</td>
</tr>
<tr>
<td>MAR</td>
<td>Missing at random</td>
</tr>
<tr>
<td>MCAR</td>
<td>Missing completely at random</td>
</tr>
<tr>
<td>MI</td>
<td>Measurement invariance</td>
</tr>
<tr>
<td>MS</td>
<td>Mover-Stayer model</td>
</tr>
<tr>
<td>OSR</td>
<td>Opportunities, Supports, and Resources, a facet scale of the WRI</td>
</tr>
<tr>
<td>PC-A</td>
<td>Personal Characteristics – Affective, a facet scale of the WRI</td>
</tr>
<tr>
<td>PC-B</td>
<td>Personal Characteristics – Behavioral, a facet scale of the WRI</td>
</tr>
<tr>
<td>PC-C</td>
<td>Personal Characteristics – Cognitive, a facet scale of the WRI</td>
</tr>
<tr>
<td>POB</td>
<td>Positive organizational behavior</td>
</tr>
<tr>
<td>PsyCap</td>
<td>Psychological Capital</td>
</tr>
<tr>
<td>PWB</td>
<td>Psychological well-being</td>
</tr>
<tr>
<td>RMSEA</td>
<td>Root mean square error of approximation</td>
</tr>
<tr>
<td>SDT</td>
<td>Self-Determination Theory</td>
</tr>
<tr>
<td>SRP-A</td>
<td>Self-Regulatory Processes – Affective, a facet scale of the WRI</td>
</tr>
<tr>
<td>SRP-B</td>
<td>Self-Regulatory Processes – Behavioral, a facet scale of the WRI</td>
</tr>
<tr>
<td>SRP-C</td>
<td>Self-Regulatory Processes – Cognitive, a facet scale of the WRI</td>
</tr>
<tr>
<td>WRI</td>
<td>Workplace Resilience Inventory (McLarnon &amp; Rothstein, 2013)</td>
</tr>
</tbody>
</table>
Resiliency and Well-being: Trajectories of Change Over Time

Resiliency is often considered as an attribute that can assist an individual in overcoming adversity and challenging circumstances. As an intuitively important attribute, the psychological community began the scientific study of the phenomenon of resiliency in the early 1980s, and reports invoking conceptualizations of resiliency are common throughout the popular media. Since the early work on resiliency by Werner and Smith (1982, 1992), the literature has been witness to considerable growth as numerous researchers have sought to understand the nomological network of resiliency (see e.g., Richardson, 2002; Rigsby, 1994; Wald, Taylor, Asmundson, Jang, & Stapleton, 2006). However, recent calls put forth by Richardson (2002) and others, although acknowledging the contribution of these extensive correlational taxonomies, have advocated the further investigation of how resiliency functions. Thus, despite the development and refinement of a nomological network around resiliency (which includes personal characteristics, demographic variables, life experiences, etc.), the processes behind resiliency and the mechanisms that promote well-being in the face of adversity have yet to be sufficiently studied. Therefore, the current research is focused on exploring the dynamic nature of resiliency over time by investigating two broad questions. First, why is resiliency necessary? And second, how does resiliency progress over time? Answers to these research questions will be able to inform the development of training programs, which may potentially increase an individual’s resiliency, and lead to enhanced well-being following adverse and challenging events.

The study of resiliency in organizational contexts is essential because the landscape of the modern organization is often described as ever-changing and tumultuous (e.g., Kenexa, 2012; Salas & Gelfand, 2013). Furthermore, common reports on employment experiences highlight the impact of downsizing, doing more with less, adjusting to change, and failing to
meet business objectives (see Coffman, & Gonzalez-Molina, 2002; Luthans, Norman, Avolio, & Avey, 2008). It has, however, been proposed that individuals ‘with more resiliency’ will be better equipped for the challenges and adversities of the modern workplace (Coutu, 2002). Therefore, investigating the nature of resiliency holds much promise for understanding how individuals may function effectively in the face of challenging and adverse workplace events.

The term turmoil could easily be used to describe the current state of the global economy. D. J. Q. Chen and Lim (2012) have recently gone as far as to say that the United States is suffering from the highest rate of unemployment since the Great Depression of the 1930s. Unfortunately, despite a downward trend in unemployment rates since the economic crisis of 2008, Canada has not been immune to these effects either as unemployment rates have oscillated month-to-month (Labour Force Survey, 2013). Thus, employment may be far from certain for recent graduates and seasoned employees alike. In an age where employment changes are frequent, it is critical to understand how the well-being of individuals searching for employment is impacted during the job search process.

Following an adverse event, it is proposed that an individual will rely on a range of protective factors and processes to return to his or her previous level of performance and well-being. These protective factors and processes define resiliency. Although recent research has begun to map the resiliency construct and demonstrate its role in influencing positive individual and organizational outcomes, the study of resiliency is still in its infancy (Luthans, Youssef, & Avolio, 2007). In order to maximize the understanding available in the literature on the nature and theoretical functioning of resiliency, several important lines of research must be embarked upon. As such, this research had two broad aims. First, to gain a better understanding of the characteristics of adverse and challenging events that necessitate demonstrating resiliency, I will explore how changes in basic psychological need satisfaction
relate to changes in resiliency and its dynamic nature. Second, the longitudinal trajectory of resiliency, as it unfolds in response to a specific challenging event, namely getting laid off, will be investigated. These two studies will enable an enhanced understanding of the processes and mechanisms of resiliency, and may help inform the literature as to how and why resiliency functions. In subsequent research, this knowledge will be integral for the development of training programs or interventions motivated to improve resiliency in individuals.

The remainder of this Introduction is separated into two major sections. First, I will outline the current state of resiliency research in organizational contexts. This will focus on an overview of the Psychological Capital (PsyCap; Luthans, Youssef et al., 2007) construct and theory. It is necessary to provide a detailed review of PsyCap because it is the dominant theoretical perspective on resiliency that has permeated the organizational literature. Although the PsyCap model has amassed considerable support in the organizational literature, several theoretical and methodological shortcomings of the PsyCap model and current body of literature will also be discussed. Then, in the second major portion of this Introduction, I will build upon these shortcomings, and review the conceptual model of King and Rothstein (2010). This discussion is meant to position the King and Rothstein model of resiliency as superior as compared to the PsyCap because it presents a more comprehensive and theoretically-integrated view of resiliency.

Resiliency in the Organizational Literature

The study of resiliency, which resides within the domain of positive organizational behavior (POB), has recently been gaining attention from academic and practitioner audiences (Luthans, Youssef et al., 2007; see also e.g., Wright & Quick, 2009). Luthans and colleagues initiated one of the major branches of inquiry into POB (see Luthans, 2002a,
2002b; Luthans & Youssef, 2007) to better understand and appreciate well-being and functioning at work. Luthans and colleagues argued that POB should focus on the strengths and capacities of individuals that can lead to adaptation and positive outcomes for individuals and organizations, rather than the more common negative or problem-focused approach. In building upon the seminal work of Seligman and colleagues on positive psychology (e.g., C. Peterson, 2006; C. Peterson & Seligman, 2004; Seligman, 1998; Seligman, & Csikszentmihalyi, 2000), Luthans and colleagues devised the higher-order PsyCap construct. PsyCap has been defined as “an individual’s positive psychological state of development that is characterized by (a) having confidence (Self-Efficacy) to take on and put in the necessary effort to succeed at challenging tasks; (b) persevering toward goals and, when necessary, redirecting paths to goals (Hope) in order to succeed; (c) making a positive attribution (Optimism) about succeeding now and in the future; and (d) when beset by problems and adversity, sustaining and bouncing back and even beyond (Resilience) to attain success” (Luthans, Youssef et al., 2007, p. 3). Thus, the PsyCap model represents not only the functioning of Resiliency, but also that of Hope, Self-Efficacy, and Optimism.

Luthans and colleagues (e.g., Luthans et al., 2007; S. J. Peterson, Luthans, Avolio, Walumbwa, & Zhang, 2011) have suggested that PsyCap should be conceptualized as a single, higher-order construct, such that each of the four capacities function in a synergistic manner to affect positive outcomes. Luthans and colleagues (e.g., Luthans, Avey, Avolio, Norman, & Combs, 2006; Luthans, Avolio, Avey, & Norman, 2007; Luthans, Avolio, Walumbwa, & Li, 2005) have suggested that PsyCap may produce higher correlations with outcomes of interest than any of the constituent facets because it is a construct that should be considered in terms of the ‘whole may be greater than the sum of its parts.’
Based on the conservation of psychological resource (COR) theory (see Hobfoll, 1989, 2002), Avey, Reichard, Luthans, and Mhatre (2011) have discussed the theoretical basis for this higher-order conceptualization. COR theory proposed that well-being is maintained or gained when an individual is able to protect his or her personal resources. Personal resources can consist of a wide-range of personal attributes or characteristics, events or experiences in the environment, values, and significant social relations. COR further states that well-being will decrease when resources are lost. For example, well-being may decrease because of failing an exam at school, which thereby decreases levels of self-efficacy. COR states that since one’s self-efficacy is now lower, well-being will also be lower because an individual has lost that, or at least a proportion of, sense of efficacy. Avey et al. suggested PsyCap is better considered as a singular construct because the coping mechanisms of hope, self-efficacy, optimism, and resilience are complementary, and share considerable commonality. In this sense, each of the four capacities associated with the PsyCap model are simply indicators of a broader, omnibus core factor, which integrates the functioning the four capacities to achieve positive outcomes (Dawkins, Martin, Scott, & Sanderson, 2013). This singular conceptualization is also aligned with COR theory, in that Hobfoll (2011) has argued that personal resources are unlikely to operate independently, and should be considered in “caravans,” which represent the combined functioning of diverse resources to impact well-being. In several instances Luthans and colleagues have explicitly stated that PsyCap is a singular construct, despite encompassing a diverse set of facet-level constructs (e.g., Avey et al., 2011; Luthans, Youssef et al., 2007).

PsyCap has also been described as a state-like construct, which is open to change and development, but may also display some consistency across environments and situations (Avey, Luthans, & Youssef, 2010). Luthans and Youssef (2007) have advocated for such a
state-like conceptualization to help position the PsyCap construct between states and traits. As such, Luthans and Avolio (2009) argued for considering PsyCap as a mid-range theory. Mid-range theories help bridge the gap between trait and state constructs, which is the conceptual domain many previous resiliency and well-being theories occupy (see Haase, 2007). For example, in a discussion of a multifaceted conceptualization of resiliency, Masten and Reed (2002; see also Masten & Wright, 2009) have shed light on the dynamic and stable attributes that are positively related to individuals’ adaptation to adverse events. Furthermore, Masten (2001) summarized that numerous protective factors (i.e., trait-like constructs) in tandem with adaptational processes (i.e., state-like constructs) influence well-being and recovery from adverse events (see also Masten, Best, & Garmezy, 1990; Werner & Smith, 1982, 1992). Thus, occupying somewhat of a middle ground between pure states and pure trait constructs, the capacities associated with resiliency, and PsyCap, may be best considered as state-like, and encompass the functioning of both traits and states to affect outcomes (see Hunter & Chandler, 2007).

**PsyCap Research Evidence**

Given the theoretical and conceptual foundations for the PsyCap construct, investigations into the relations between PsyCap and important individual and organizational outcomes are intuitively appealing because those that have more positive strengths and capacities should be able to perform better. The construct of PsyCap has received considerable research attention, and the body of literature surrounding the construct has demonstrated several important findings.

Avey, Luthans, and Jensen (2009) demonstrated that PsyCap exhibited a significant negative relation with stress symptoms ($r = -0.35$, $p < .01$) in a sample of 360 university employees. Avey et al. (2009) also noted that PsyCap was significantly related to intentions
to quit ($r = -.29, p < .01$) and intentions to search for a new job ($r = -.20, p < .01$). This suggested that bolstering employees’ positive attributes and resiliency might limit turnover and reduce the dysfunctional effects of stress. Additionally, in a sample of 280 university employees, Avey, Luthans, Smith, and Palmer (2010) provided evidence for significant relations between PsyCap and psychological well-being ($r = .47, p < .01$) and physical health ($r = .24, p < .01$). Avey, Luthans, Smith et al.’s results suggested that PsyCap can help explain both positive and negative personal outcome variables to a substantial degree.

Luthans and colleagues have also investigated the relation between PsyCap and other more focal organizational criteria. Across three samples, Luthans, Avolio et al. (2007) found that PsyCap was significantly related to job performance and job satisfaction. In the first sample, drawn from management students from two universities ($n = 404$) PsyCap was found to correlate at $.39 (p < .01)$ with job satisfaction and $.25 (p < .01)$ with self-rated job performance. Luthans, Avolio et al. (2007) also found that PsyCap correlated at $.32 (p < .01)$ with job satisfaction in a sample of 115 manufacturing employees and at $.53 (p < .01)$ in a sample of service employees. In these two samples, PsyCap’s relation to job performance was assessed in relation to an overall assessment of performance obtained from combined supervisor ratings and objective data. The correlation between PsyCap and performance for the manufacturing employees was $.33 (p < .01)$, and $.22 (p < .05)$ for the service employees.

Although supervisor ratings and objective data represent important components of the job performance domain (Campbell, Gasser, & Oswald, 1996), Avey, Luthans, and Youssef (2010) also investigated how PsyCap related to additional aspects of performance: organizational citizenship behaviours (OCBs) and counterproductive work behaviours (CWBs). Avey, Luthans, and Youssef found that the PsyCap was correlated with self-rated CWBs, and interpersonally- and organizationally-directed OCBs at $.50, .40, .58 (ps < .01; n
Further, Avey, Luthans, and Youssef found that PsyCap accounted for significant amounts of incremental variance above and beyond demographics, personality, and person-environment fit in the prediction of CWBs and both measures of OCB. Further, Walumbwa, Luthans, Avey, and Oke (2011) demonstrated that a leader’s authentic and transformational leadership styles were positively and significantly related to his or her subordinates’ PsyCap, $r = .31$ and $.39$, respectively ($p < .01$; see also Gooty, Gavin, Johnson, Frazier, & Snow, 2009).

Finally, Avey et al. (2011) undertook a meta-analytic summary of these research findings. Avey et al. noted that the relations between PsyCap and job satisfaction ($\rho = .45$), commitment ($\rho = .40$), turnover intentions ($\rho = -.28$), stress ($\rho = -.20$), citizenship behavior ($\rho = .43$), job performance ($\rho = .26$), and counterproductive behavior ($\rho = -.43$). Additionally, Avey et al. summarized the relation between PsyCap and psychological well-being ($\rho = .40$). As these relations were fairly moderate in strength (e.g., Cohen, 1988), Avey et al. suggested that they underscored the importance of PsyCap as a predictor of employees’ well-being.

Taken together, these studies investigating the role of PsyCap in employee health and well-being, job attitudes, job performance, and leadership suggest important relations between PsyCap and personal and organizational outcome variables. As well, these results should encourage continued POB scholarship, and by association, the further study of resilience in relation to key organizational and personal outcome variables.

Although these PsyCap findings present several notable contributions to the POB literature, as will be reviewed later, PsyCap may not tap an adequate conceptualization of resiliency. Further, the research reviewed above presented a limited understanding of PsyCap’s state-like nature. Therefore, I will next outline the evidence supporting the malleable nature of PsyCap.
PsyCap over Time

Turning now to a more targeted review around the research questions at the focus of my dissertation, several empirical studies by Luthans and colleagues have documented evidence supporting the malleable nature of PsyCap. Of note, Avey, Luthans, and Mhatre (2008) recently put forth a call for positive psychology researchers to pursue longitudinal research questions. Such investigations would be positioned to examine the role of time in the mechanisms proposed by positive psychology to influence well-being and performance. Using a longitudinal study and latent growth modeling (LGM), S. J. Peterson et al. (2011) demonstrated that PsyCap does indeed fluctuate over time. S. J. Peterson et al. also found a significant positive relation between changes in PsyCap over time and subjective (supervisor ratings) and objective (sales revenue) measures of job performance. These findings provide two noteworthy contributions to the knowledge available on PsyCap. First, the finding that PsyCap changes over time provides evidence for the state-like nature of the construct. Second, demonstrating a positive relation between change in PsyCap and performance would suggest that increasing levels of PsyCap would, in turn, increase one’s level of performance.

The results of S. J. Peterson et al. (2011), however, presented an interesting finding in terms of the rate at which PsyCap changes over time. S. J. Peterson et al. found that over a six-month period the average change in PsyCap was negative (i.e., $\mu_{\text{Latent Slope}} = .07, p < .05$). S. J. Peterson et al. argued that the negative rate of change should be expected because individuals (in the financial advising sector – presumably under considerable pressure and stress following the 2008 economic meltdown) were only expending their psychological resources. S. J. Peterson et al. further aligned these finding with the propositions of COR theory (Hobfoll, 2002; Wright & Hobfoll, 2004). S. J. Peterson et al. highlighted the notion that as individuals did not have an opportunity to develop any PsyCap resources (e.g.,
through a PsyCap intervention or substantial break from work [Kühnel & Sonnttag, 2011]), they were continually drawing upon their (finite) PsyCap resources, which ultimately led to a decrease in level over time.

A second line of research on the malleability of PsyCap comes from two studies documenting the change in PsyCap following an intervention. Luthans, Avey et al. (2006) first proposed the development of a PsyCap intervention. They noted that a focused intervention, as brief as two hours, may be able to influence and bolster individuals’ PsyCap resources. Focusing on the effects the proposed intervention is hypothesized to have on the Resiliency facet only, Luthans, Avey et al. noted that the intervention targets developing the “cognitive, emotional, and behavioral processes” (p. 390) associated with enhancing personal resiliency skills and minimizing risk factors (lack of mentors, not actively avoiding potentially adverse events). As part of the intervention protocol, participants identify their immediate reactions to a setback or adverse event, and then in conjunction with the intervention facilitator, elaborate on how to ideally mentally frame the setback by focusing on what is under their control, and what potential options for action might be. Luthans, Avey et al. further noted that through the intervention, individuals are encouraged to anticipate and address potential setbacks, increasing their ability to deal with impending challenging events.

From preliminary estimates, Luthans, Avey et al. (2006) reported that the intervention was able to raise PsyCap levels by three percent (stated as “statistically significant”; p. 391) in a pre-/post-testing design as compared to a control group. Using the same PsyCap intervention of Luthans, Avey et al., Luthans, Avey, and Patera (2008) sought to investigate the effectiveness of an intervention that was administered online in a self-guided manner.

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1 It is beyond the scope of the current research to review in detail how the PsyCap intervention targets the other three facets, but as discussed by Luthans, Avey et al. (2006), each facet is targeted individually with specific and independent exercises and activities.
Using a large experimental sample, divided into a treatment \((n = 187)\) and control group \((n = 177)\), results further supported the notion that the PsyCap capacities are malleable, and that the intervention increased PsyCap levels. Of note, Luthans, Avey et al. only documented a significant change in PsyCap for the experimental treatment group, whereas there was no significant change for the control group. Luthans, Avey et al. concluded that PsyCap is indeed a developable construct that demonstrates state-like properties, and proposed PsyCap interventions would likely assist organizations and individuals in achieving positive outcomes.

Subsequently, Luthans, Avey, Avolio, and Peterson (2010) sought to replicate and extend the findings of Luthans, Avey et al. (2008) by examining the effects of the PsyCap intervention and the resulting change in job performance. Luthans et al. (2010) also found that PsyCap level increased significantly following the PsyCap intervention. Supervisor- and self-rated Performance was also found to be significantly higher following the intervention. These results provide further evidence for the state-like nature of PsyCap. Furthermore, these results demonstrate that increasing an employee’s level of PsyCap results in an improvement of supervisor- and self-rated job performance.

Although PsyCap and resiliency are associated with POB, a more general review of positive psychological interventions available in the literature also highlights evidence for the state-like functioning of constructs associated with POB. In general, this body of research has shown that increasing levels of POB constructs can positively influence individual well-being (e.g., Brunwasser, Gillham, & Kim, 2009; Gillham, Hamilton, Freres, Patton, & Gallop, 2006; Steinhardt & Dolbier, 2008). In a recent review, Meyers, van Woerkom, and Bakker (2013) found that 86% of studies examining the effectiveness of a positive psychological intervention found a significant positive impact on well-being. Of note, Meyers et al.
concluded, “positive psychological interventions in the working context consistently enhance employee well-being, which is a crucial finding for organizations” (p. 10). In sum, the constructs subsumed by POB and positive psychology have generally been found to be of a state-like nature and are open to development. Further, increases in these constructs are associated with positive changes in important outcome variables.

The focus of the literature reviewed so far has been in line with the theoretical propositions of Luthans and colleagues. Thus, although the PsyCap facets are quite diverse in nature, PsyCap is considered a unitary, superordinate construct that encompasses the functioning of Hope, Optimism, Self-efficacy, and Resiliency. In fact, Luthans et al. (2010) have noted that it was impossible to determine “whether one or more of the psychological capital components differentially created the effects found” (p. 59). This limitation will be discussed in further detail later, but two theoretical reviews (discussed below) published by supporters of PsyCap discuss the specific state-like and malleable nature of resiliency.

The General State-like Nature of Resiliency

With a focus on resiliency in workplace contexts, but separate from the theory supporting PsyCap, two theoretical reviews have recently considered the role of resiliency as a distinct, state-like, and developable construct. First, Luthans, Avey et al. (2006) discussed two frameworks, proactive and reactive, for the development of resiliency in individuals in the workplace. Second, Fleig-Palmer, Luthans, and Mandernach (2009) outlined the process of resiliency development during reemployment.²

Luthans, Avey et al. (2006) noted that the development of resiliency-related skills could be considered a vital human resource function. They argued that the ability to

² Although the Luthans, Avey et al. (2006) article is the same as the one discussing the PsyCap intervention, they approach the notion of resiliency development from a more general perspective than that defined by the PsyCap construct. The Fleig-Palmer et al. (2009) article also proposed a more general resiliency concept than that of the PsyCap.
overcome adversity and display adaptation in the face of setbacks is imperative to maintaining effective levels of performance and well-being in the modern economy (see also Hamel & Valikangas, 2003). Furthermore, Luthans, Avey et al. suggested that specifically enhancing employees’ resiliency would be enabled because of its state-like, and developable nature (Bonanno, 2004; Masten, 1994, 2001; Masten & Reed, 2002; Youssef & Luthans, 2005). Given the need for resiliency in the workplace, and the potential to improve resiliency, Luthans, Avey et al. proposed two approaches organizations could use to increase resiliency.

First, the proactive approach anticipates employees’ need for resiliency and provides adequate organizational supports to do so. The proactive approach encompasses risk-focused strategies that reduce the risk of stress, asset-focused strategies that enhance positive attributes and protective factors, and process-focused strategies that rely on ensuring a workforce is able to effectively problem-solve. The second approach is reactive and encompasses strategies that encourage employees to focus on positive thoughts and emotions, and to find meaning in negative events. In sum, Luthans et al. outlined how the resiliency of employees could be bolstered by focused organizational interventions that target employees’ ways of thinking, feeling, and behaving. Indeed, Norman, Luthans, and Luthans (2005) have discussed a recent movement for large organizations (e.g., Hewlett Packard) to offer resiliency training to employees to enhance the effectiveness of their workforce.

Fleig-Palmer et al. (2009) aimed to apply resiliency theory (without reference to a particular theory) to the job search and reemployment literature. They posited that individuals with higher resiliency would be more likely to conduct a more effective job search. Fleig-Palmer et al. also noted that resiliency would likely play an important role in the job search not only for individuals undergoing the reemployment and job transition process, but also for individuals breaking into the workforce (e.g., college students
RESILIENCY AND WELL-BEING

attempting to get their first job, Arnett, 2004; immigrants adjusting to new workplace norms or contending with underemployment scenarios; Feldman, 1996; Guerrero & Rothstein, 2012). Fleig-Palmer et al. noted, “resiliency, therefore, can assist in providing important insight into the job search and reemployment process” (p. 234) and suggested that resiliency, if developed could enhance job search and employment outcomes. Thus, the propositions of Fleig-Palmer et al. suggested the importance of considering resiliency in organizational contexts to address issues related to the job search process and well-being, and that resiliency has several state-like attributes that are open to change.

Taken together, resiliency, in general, may demonstrate several malleable attributes and can be considered a state-like construct that is open to change and development. It has been critical to review this literature to set the stage for both studies comprising my dissertation. In particular, Study 2 followed, over the duration of the career transition process, individuals who have been laid off to map the trajectory of change in resiliency.

Although this review has discussed the general theoretical perspectives on the state-like nature of resiliency, they may not be very applicable to PsyCap because of several theoretical and methodological shortcomings in the PsyCap model. The next section of this Introduction will focus on several of these shortcomings, which I am to highlight to suggest that PsyCap may not tap an adequate conceptualization of resiliency. Although I do present several shortcomings, the studies completed with PsyCap have revealed many interesting and important findings, and as such I do not wish to portray PsyCap as flawed, but would instead propose that more attention needs to be paid to the explicit conceptualization of resiliency. Thus, my focus here is on the meaning, measurement, and use of the Resilience facet of the PsyCap model.
Shortcomings of the PsyCap Model and its Resilience Facet

As noted, resiliency has been considered as an integral aspect of Luthans, Youssef et al.’s (2007) PsyCap model. Luthans and colleagues have conceptualized resiliency as “the developable capacity to rebound or bounce back from adversity, conflict, or failure” (p. 18). Luthans and colleagues proposed that resiliency functions to restore well-being and positively impact outcomes (e.g., satisfaction, commitment; see e.g., Luthans, Avey et al., 2008) after the experience of an adverse event. However, as I described in McLarnon and Rothstein (2013), there are several shortcomings with this conceptual definition, which may hinder the study, accumulation of knowledge, and practical applications of resiliency.

Focusing on the definition provided by Luthans, Youssef et al. (2007) suggests at least three limitations. First, defining and operationalizing resiliency as simply bouncing back to a previous state of functioning does not explain how this bouncing back actually occurs. The processes and mechanisms that actually influence overcoming adversity and returning to a previous state of functioning and well-being are not defined. The early work of Garmezy (1981, 1991), Masten (1994, 2001; Masten & Reed, 2002), and Werner and Smith (1982, 1992) would suggest that following an adverse event, individuals will engage in emotional, behavioral, and cognitive adjustments to help cope with the event and return him or her to a desired level of well-being and performance. Thus, based on this early work in the clinical and developmental domains, resiliency may be better conceptualized as inclusive of a series of active and effortful processes, working alongside automatic mechanisms, to affect changes in well-being and performance following the experience of an adverse event.

Second, PsyCap’s concept of resiliency suggests a unidimensional construct (Luthans, Youssef et al., 2007). Luthans and colleagues have noted that the resilience component of the PsyCap models is a singular construct that taps the capacity to ‘bounce back’. The early work
on resiliency (cited above) would suggest that a multitude and diversity of individual differences (often labeled as protective factors) are associated with achieving positive outcomes in the face of adversity. For example, children who demonstrated protective factors such as viewing experiences constructively, using an active approach to solving life’s problems, and obtaining positive attention from others, were consistently shown to be better adjusted than peers who were facing similar hardships (Werner, 1993). Furthermore, as the empirical investigation into the nature of resiliency grew, additional protective factors and indicators of resiliency were highlighted. This included individual competence (Garmezy, Masten, & Tellegen, 1984; Masten, 1994; Masten et al., 1990), self-esteem and self-help (Garmezy, 1981), continual growth and adaptation to change (Rutter, 1985), coping skills (Garmezy, 1991), communication and problem-solving skills (Hauser, Vieyra, Jacobson, & Wertlieb, 1985), positive aspects of one’s social influences, and a supportive family environment (Rutter, 1987). More recently, several authors like Richardson (2002) and Wald et al. (2006) have aimed to integrate these findings, and build a taxonomy of the individual differences associated with resiliency. One author has even suggested this taxonomy resembles a “laundry list” (Haase, 2007, p. 350). The point here is that, resiliency, as conceptualized by many authors and supported by many empirical studies, would suggest a multidimensional construct. This may suggest that the PsyCap model of resiliency may lack conceptual depth and may not be adequately aligned with many of the theoretical standpoints and propositions on resiliency.

Third, the higher-order conceptualization of PsyCap may be especially problematic because it is inconsistent with theory-building that places an emphasis on the individual PsyCap facets in particular scenarios. As an illustration, Youssef and Luthans (2005), exploring the relation between resiliency and leadership, proposed “leaders’ self-efficacy
partially mediates the relationships between their assets, risk factors, and values and their resiliency” (p. 321). Investigating this hypothesis would seemingly contradict the propositions underlying the higher-order PsyCap model. Specifically, adhering to the notion of the ‘whole is greater than the sum of its parts’ logically precludes the possibility of investigating the individual role of any of the PsyCap facets.

Interestingly, although the majority of PsyCap research has used the higher-order construct, one study examined the contribution of each facet. Examining the relation between PsyCap and supervisor-rated job performance of factory workers ($n = 422$), Luthans et al. (2005) found that PsyCap correlated with performance at .26 ($p < .01$). Yet, they also noted that the correlation between PsyCap’s Resiliency scale and performance was .24 ($p < .01$). According to Meng, Rosenthal, and Rubin’s (1992) test of correlated correlation coefficients these relations are of equal strength, $z = .64, p = .53$. This would suggest that although PsyCap demonstrates a statistically significant relationship with job performance, an equivalent and equally useful correlation is observed with PsyCap’s Resilience scale. Further, one could interpret this as evidence that does not support Luthans, Avey et al. (2006) proposition that the whole is greater than the sum of its parts.

My review suggests that the conceptualization of resiliency provided by PsyCap is lacking. However, a recent theoretical framework of resiliency proposed by King and Rothstein (2010) addresses several of PsyCap’s limitations, further integrates previous theories of resiliency, and as such, will be invoked as the resiliency framework guiding this dissertation.

**The King and Rothstein (2010) Model**

The King and Rothstein (2010) model of resiliency specifies the attributes and mechanisms that may enable individuals to recover and thrive in the face of adversity. This
RESILIENCY AND WELL-BEING

model defines resiliency as a set of protective factors and dynamic self-regulatory processes that unfold over time. King and Rothstein conceptualized resiliency as involving protective factors and self-regulatory processes, both divided into affective, behavioral, and cognitive components that can help restore optimal functioning, and facilitate adaptation after a significant adverse experience. The model was developed to capture the key elements and processes involved in recovering from failure, disillusionment, and disappointment.

Conceptualized as more integrated and comprehensive than previous theoretical models, King and Rothstein suggested that resiliency, as a dynamic process, involves the combined role of several individual differences variables and several environmental variables (see Luthar, Cicchetti, & Becker, 2000). It has been proposed by King and Rothstein and McLarnon and Rothstein (2013) that this dynamic, process-oriented model may provide a more comprehensive treatment of the attributes and processes involved with recovering from adverse experiences than alternative models of resiliency. Therefore, King and Rothstein’s model may be more ideally suited to guide examinations of adaptation in response to highly challenging experiences.

King and Rothstein (2010) developed a functional and compelling model of resiliency that may assist in studying and understanding what can help, and what can hinder in regards to performing in contemporary organizations following a significant set-back. Concisely, the King and Rothstein model of resiliency can be defined as a self-regulatory, meaning-oriented approach to the processes of recovery and personal growth following major loss in the workplace. Through the self-management of one’s thoughts, feelings and actions, resiliency may be elicited in response to potentially traumatic events and experiences.

The King and Rothstein (2010) model considers resiliency as a set of protective factors and dynamic processes, which function to assist an individual in returning to a desired
level of well-being and performance (see Figure 1 for a visual representation). Resiliency is conceptualized as a multidimensional construct that incorporates the domains of affective, behavioral, and cognitive protective factors and affective, behavioral, and cognitive self-regulatory processes. These resiliency processes are invoked by one’s initial reaction to a traumatic event, and are bolstered and influenced by several individual difference protective factor variables, and a system of social supports and resources. Resiliency processes represent emotional-regulation factors, behavioral capacities, and cognitive processes, which can assist an individual recover from an adverse event. In sum, resiliency refers to the ways of feeling, thinking, and behaving that can facilitate recovery following an adverse event.

King and Rothstein (2010) proposed that resiliency is a process defined by adaptive affective, behavioral, and cognitive responses to adversity. These adaptive responses, if successful, will lead to outcomes that demonstrate resilience having occurred, but these outcomes may be quite different depending on the situational context and the adversity experienced. Resiliency, as conceptualized by King and Rothstein, focuses on the process of recovering from an adverse event, and as such, can be considered predictors of resiliency-related outcomes (e.g., well-being, career success). In other words, resiliency is the process by which well-being is restored, rather than the end point one arrives at following an adverse event.

The King and Rothstein (2010) framework proposes that protective factors and processes can be conceptualized in terms of affective, cognitive, and behavioral domains, involving (a) self-regulation of emotions, (b) beliefs or cognitive strategies that provide a sense of coherence or meaning, and (c) behavioral strategies that provide a sense of personal control and personal self-efficacy (Brandtstädter, 1998; King, Brown, & Smith, 2003;
Decomposing the King and Rothstein model highlights eight constituent facets that can be defined as:

**Initial responses.** Initial reactions toward traumatic events and circumstances; the content of this domain includes the interpretation of events and resulting disequilibrium, or change from a previous state of functioning and well-being.

**Affective personal characteristics.** Individual characteristics and protective factors that provide a sense of emotional well-being and self-esteem; the content of this domain includes the abilities to maintain a stable sense of self, sense of personal worth, and being able to reason with and understand emotions while not succumbing to extreme emotions, or being easily made upset.

**Behavioral personal characteristics.** Individual characteristics and protective factors that provide a sense of agency or personal control; the content of this domain includes self-efficacy, diligence, self-discipline, aspiring for challenging goals, striving to attain goals, and being competent and capable of dealing with challenges.

**Cognitive personal characteristics.** Individual characteristics and protective factors that provide a sense of coherence or meaning; the content of this domain includes active learning and seeking out new experiences and encounters, and actively examining and ascribing meaning to experiences, as well as being open-minded and attentive.

**Opportunities, supports, and resources.** Sources and availability of social support and resources; the content of this domain includes availability and support from close social relationships (family, significant other, community, workplace relationships, etc.).

**Affective self-regulatory processes.** Mechanisms related to controlling and regulating emotions; the content of this domain includes processes associated with emotion-based decision making, analyzing one’s affective state, and emotional regulating processes.
Figure 1. General conceptual model of the Workplace Resilience Inventory. Adapted from King and Rothstein (2010) and McLarnon and Rothstein (2013). Dashed lines indicate the role of a significant, challenging event, and indicates under what conditions resiliency may be necessary. Solid lines indicate relations between resiliency components and important outcome variables.
**Behavioral self-regulatory processes.** Mechanisms related to understanding and controlling negative and ineffective behaviors; the content of this domain includes processes associated with impulse control, planfulness, self-discipline, and self-observation.

**Cognitive self-regulatory processes.** Mechanisms related to understanding and controlling negative and ineffective thoughts and thinking patterns; the content of this domain includes processes associated with resourcefulness, cognitive flexibility (willingness to compromise, accommodate, and consider others’ perspectives), seeing experiences in a positive light, and minimizing intrusive thoughts.

Thus, the attributes and processes tapped by King and Rothstein’s (2010) model present an integrated and comprehensive perspective on achieving positive outcomes and well-being in the face of significant adversity.

**Measurement of King & Rothstein’s (2010) Model of Resiliency**

Work conducted by McLarnon and Rothstein (2013) laid the groundwork for the investigations comprising this dissertation. Specifically, McLarnon and Rothstein’s study involved the development and initial efforts of validating a multidimensional measure of resiliency (the Workplace Resiliency Inventory; WRI), as outlined by King and Rothstein (2010). The WRI consists of 60 items that assess all eight facets of resiliency. McLarnon and Rothstein’s study revealed strong estimates of reliability, and many strong bivariate and multivariate relations between the WRI facets and several important well-being criterion variables (i.e., depression, perceived stress, and life satisfaction). Table 1 contains example items for each of the WRI’s scales, the number of items on each scale, and the estimates of Cronbach’s $\alpha$ for each scale from McLarnon and Rothstein, as well as from the subsequent studies of Halliday (2013) and Kisinger (2012).
Thus, the WRI is a psychometrically-sound and informative tool that may assist with examinations into the resiliency of individuals. Further, by tapping the more comprehensive and theoretically-integrated model of resiliency (King & Rothstein, 2010), the WRI may offer more ecologically valid insights into the functioning of individuals following adverse experiences. This may offer researchers and practitioners stronger estimates of relations between resiliency and important outcome variables. Nevertheless, the King and Rothstein model and the WRI are based on the functioning of several components of a dynamic, process-based model of resiliency, and to this end, the current studies were designed to investigate the nature of adverse experiences that may necessitate resiliency, and to investigate how resiliency changes over time.

**Current Studies**

The current studies are centered on answering research questions of a predominantly longitudinal nature to a) integrate Self-Determination Theory (SDT; Deci & Ryan, 1985) need satisfaction with resiliency to offer an understanding of why resiliency may be necessary, and b) map the trajectory of resiliency after the experience of a challenging event. In brief terms, to be expanded upon in more detail below, Study 1 seeks to examine the relation between changes in need satisfaction (see Deci & Ryan, 2000) and the changes in resiliency over time. Study 2 then seeks to examine the dynamic nature of resiliency over time after having been fired from one’s job. These two studies are, broadly speaking, designed to satisfy Ployhart and Vandenberg’s (2010) requirements for demonstrating evidence to support dynamic, longitudinally-oriented theories. In particular, Ployhart and Vandenberg noted that theories involving change require that the form of change be specified (e.g., linear, nonlinear), the reasons for why the change occurs be illuminated, and the outcomes of change be discussed.
Table 1

*Example WRI scale content*

<table>
<thead>
<tr>
<th>WRI Facet</th>
<th>Example Item</th>
<th># of Items</th>
<th>Cronbach’s α</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial Responses</td>
<td>Following the event I was able to maintain a positive outlook on things.</td>
<td>6</td>
<td>.85</td>
</tr>
<tr>
<td>Affective Personal Characteristics</td>
<td>I understand why my emotions change.</td>
<td>9</td>
<td>.87</td>
</tr>
<tr>
<td>Behavioral Personal Characteristics</td>
<td>I handle tasks effortlessly.</td>
<td>9</td>
<td>.83</td>
</tr>
<tr>
<td>Cognitive Personal Characteristics</td>
<td>I am able to put a new perspective on adversities.</td>
<td>8</td>
<td>.84</td>
</tr>
<tr>
<td>Opportunities, Supports, &amp; Resources</td>
<td>I know there is someone I can depend on when I am troubled.</td>
<td>5</td>
<td>.96</td>
</tr>
<tr>
<td>Affective Self-Regulatory Processes</td>
<td>Since the adverse event I have paid closer attention to the causes of my emotions.</td>
<td>5</td>
<td>.76</td>
</tr>
<tr>
<td>Behavioral Self-Regulatory Processes</td>
<td>Since the adverse event I have often jumped into things without thinking through them.*</td>
<td>9</td>
<td>.82</td>
</tr>
<tr>
<td>Cognitive Self-Regulatory Processes</td>
<td>Since the adverse event it has been easy for me to look on the &quot;bright side.&quot;</td>
<td>9</td>
<td>.86</td>
</tr>
</tbody>
</table>

*Note.* * reverse-keyed item.
Study 1

Need Satisfaction and Resiliency

At the heart of Study 1 is an integration of Self-Determination Theory (SDT; Deci & Ryan, 1985) with that of the resiliency theory offered by King and Rothstein (2010). In particular, I contend that substantial changes in the level of satisfaction of the three SDT needs, in response to a challenging or adverse event, will necessitate resiliency. That is, substantial negative or downward changes in one’s SDT need satisfaction will necessitate the occurrence of resiliency. In other words, resiliency will only become active, and will exhibit its dynamic nature when an individual has experienced a drastic decrease in how highly his or her basic psychological needs are satisfied. In this way, substantial (most likely negative) changes in SDT need satisfaction will necessitate resiliency, and will activate resiliency’s dynamic nature. Events or experiences that do not significantly impact how highly one’s SDT needs are satisfied will not need to involve resiliency protective factors or resources, or activate the affective, behavioral, and cognitive self-regulatory processes of resiliency. Although this is the fundamental focus of Study 1, a number of more specific research questions and hypotheses will be proposed. However, an introduction to SDT is first necessary.

Self-determination theory background. The basic psychological needs associated with SDT have been considered three of the most important needs an individual strives to fulfill (Church et al., 2012; Deci & Ryan, 1985, 2000, 2008; Deci, Ryan, Gagné, Leone, Usunov, & Kornazheva, 2001; Patrick, Knee, Canevello, & Lonsbary, 2007; Ryan & La Guardia, 2000; Sheldon, Elliot, Kim, & Kasser, 2001; Sheldon & Niemiec, 2006; Sheldon, Ryan, & Reis, 1996). SDT delineates the role of three needs in the determination of an individual’s well-being: the needs for autonomy, competence, and relatedness.
The need for autonomy refers to the feeling that one is in control of his or her own actions (i.e., intrinsically motivated), as opposed to feeling as if external forces are the motivation for one’s actions (i.e., extrinsically motivated). Accordingly, Verleysen, Lambrechts, and Van Acker (2015) noted that autonomy, and the satisfaction of one’s own need for autonomy, concerns self-choice and self-control, versus being forced to do something. Moreover, Deci and Ryan (2000) proposed that each individual has an innate desire to create and control his or her own reality without external pressure to experience a sense of freedom. Thus, while the experience of independence is an important component of autonomy need satisfaction, it is also partially derived from the sense that one’s behavior “emanates from and is endorsed by oneself” (V. Kasser & Ryan, 1999, p. 937).

The need for competence refers to an individual’s innate need to feel that one is capable and effective in carrying out a desired action or behaviour. One’s need for competence may be satisfied, in part, by being able to do something well, or by demonstrating mastery over some element in the environment. Satisfaction of one’s need for competence may result in feeling pleasure due to being effective in one’s environment (Verleysen et al., 2015). This definition suggests a strong conceptual link to self-efficacy, which is an individual’s belief in his or her ability to perform a specific behaviour (Bandura, 1977, 1991). However, self-efficacy focuses on the perceived competence an individual may have in relation to performing a specific behaviour, whereas competence is an evaluation of the satisfaction derived from one’s level of self-efficacy. Further, generalized self-efficacy is better conceptualized as a belief one holds about their ability, whereas competence is the satisfaction and well-being derived from that belief.

The need for relatedness refers to the inherent need to feel belongingness and connectedness to others. One’s need for relatedness may, in part, be satisfied from
experiencing regular, meaningful, and personal contact with other individuals (i.e., friends, significant others, family, coworkers, etc.; Van den Broeck, Vansteenkiste, De Witte, Soenens, & Lens, 2010). Additionally, Deci and Ryan (2000) suggested that one’s relatedness needs can be satisfied by contributing to the development and growth of others, which will, reciprocally, encourage further growth and development for one’s own self.

SDT argues that these three basic psychological needs are innate, and when satisfied, are the building blocks of psychological well-being (Deci & Ryan, 2000). Although the three needs are inherent to human nature and well-being, there may be individual differences in terms of the relative levels of each individual’s needs (Richer, Blanchard, & Vallerand, 2002; Vallerand, 2000). Inasmuch, a certain amount of autonomy may satisfy different individual’s autonomy needs to different degrees. SDT need satisfaction has also been theorized to play a foundational role in motivation, such that satisfaction of the needs fosters autonomous motivation. However, the focus in this study is SDT’s essential role in influencing well-being. Moreover, SDT also states that well-being is a function of all three needs, in that all of them have to be satisfied in order to facilitate optimal well-being (Verleysen et al., 2015).

A substantial amount of empirical evidence has amassed supporting the notion that an individual’s well-being and ability to function optimally will depend on whether one’s SDT needs are adequately satisfied. For example, Patrick et al. (2007) noted that optimal well-being will be when each of the three SDT needs is fulfilled to a level satisfactory to each individual. Specific research results supporting this proposition can be found in the studies of Baard, Deci, and Ryan (2004) and Deci et al. (2001), which have demonstrated a positive relation between the experience of events that help to satisfy the autonomy, competence, and relatedness needs and well-being. T. Kasser and Ryan (2001) and V. Kasser and Ryan (1999) have also noted that supports given to individuals meant to bolster their autonomy,
competence, and relatedness need satisfaction resulted in significantly higher well-being. Sheldon et al. (1996) and Reis, Sheldon, Gable, Roscoe, and Ryan (2000) have demonstrated that fluctuations in the satisfaction of the SDT needs over time (i.e., day-to-day) predicted self-esteem, and physical and psychological well-being outcomes. In reviewing this literature, Ryan and Deci (2000) suggested that fulfillment of these three basic needs were strong determinative forces for an individual’s well-being (see also Ryan & Huta, 2009; Ryan, Huta, & Deci, 2008).

**Self-determination theory need satisfaction during life transitions.** Periods of transition are often seen as detrimental to well-being and may detract from the satisfaction of one’s autonomy, competence, and relatedness needs. Justice and Dornan (2001) suggested that undergoing a period of transition was a nearly universal event, such that nearly every individual, by their early 20s had been faced with a challenging life transition. Change disrupts one’s habits and behaviour, and reduces need fulfillment (see Quinn & Dutton, 2005). New environments, for example, may not foster the same need fulfillment because of different, and more challenging demands, or because the same resources are not present in the new environment.

Research on life transitions is common in the adolescent adjustment literature. In this literature, studies have aimed to understand the changes experienced during the transition from high school to university. This period of transition has been found to be a time of increased stress due to new roles and responsibilities, and exposure to new social networks (Aquilino, 2006; Laursen & Collins, 2009). As well, new university students have been generally noted to display higher levels of depression and anxiety as compared to the national average (Pryor, Hurtado, DeAngelo, Blake, & Tran, 2010). As suggested by Z. E. Taylor,
Doane, and Eisenberg (2014), these results should motivate researchers to examine potential processes that may assist individuals in successfully coping with this transition period.

One potential process that may have a role in adjustment during challenging life transitions is need satisfaction. Wintre et al. (2008), without explicitly discussing SDT, noted that upon entering a post-secondary institution, students whose social, intellectual, and physical needs were satisfied were more likely to continue enrollment and demonstrate greater well-being. Previous research has also shown that autonomy, competence, and relatedness need satisfaction is related to enhanced self-esteem (Deci, Schwartz, Sheinman, & Ryan, 1981), problem solving (McGraw & McCullers, 1979), and, in general, positive developmental outcomes (Deci, Vallerand, Pelletier, & Ryan, 1991; Vallerand, Blais, Brière, & Pelletier, 1989) in students. Thus, SDT need satisfaction may help explain adjustment and well-being after entering a new, challenging environment, such as entering university (e.g., Patrick et al., 2007; see also Deci et al., 1991). Therefore, changes in SDT need satisfaction experienced during the transition to university may be well suited to offer insight into the processes that impact well-being during challenging life transitions.

**Challenging life transitions in the industrial/organizational psychology literature.**

Employees are not immune to the challenges brought on by a life transition. One commonly discussed life transition is the process involved with newcomer adjustment (e.g., Allen, 2006; T. N. Bauer, Bodner, Erdogan, Truxillo, & Tucker, 2007; Holton, 1995; Ng & Feldman, 2007). Newcomer adjustment is the process an individual goes through as he or she transitions from a university or college environment to that of an organization. Klemme-Larsen and Bell (2013) suggested that the transition from university to organization can be particularly challenging because the demonstration of new skills will be required for adequate performance and that the social environment in an organization may be
substantially different from that of one’s university environment (Reicherts & PiHet, 2000). In fact, the transition from university to organization can be so demanding that half of all recent graduates will leave their new positions within four months (T. N. Bauer, 2010). Ng and Feldman (2007) suggested that lasting positive effects on one’s professional and personal development could be witnessed in those that successfully navigate a significant transition period.

Notably, Klemme-Larsen and Bell (2013) recently sought to integrate the newcomer adjustment literature with the PsyCap model. They suggested that those with more PsyCap might be less impacted by a challenging transition. Moreover, one attribute, that Klemme-Larsen and Bell singled out as important for successfully navigating the newcomer transition period is the ability to recover from setbacks and move forward. This would represent the role of resiliency in achieving positive outcomes during and after a transition. Thus, such theorizing helps to illustrate the importance of resiliency in navigating adverse and challenging events.

**Summary and integration.** Phases of transition are characterized by change in individuals’ circumstances, which may result in changes to how highly one’s SDT needs are satisfied. Detrimental effects to one’s well-being would likely result when an individual’s SDT needs are no longer optimally satisfied during and after the life transition. Resiliency, however, may offer the means by which individuals may more easily navigate challenging transition processes. Wong (2011) suggested that overcoming difficulties and adversities was related to how highly one’s autonomy, competence, and relatedness needs are satisfied. It stands to reason then, that those with higher resiliency may be better able to maintain their basic psychological need satisfaction and well-being despite the difficulties involved with experiencing a challenging life transition. This integration of SDT need satisfaction and
challenging life transitions helps provide a backdrop for investigating the relation between change in SDT need satisfaction and resiliency during challenging life transitions. Thus, the focal question to be addressed by Study 1 is whether a substantial change in SDT need satisfaction, after the experience of a challenging life transition, is related to changes in resiliency.

**Recent Self-Determination Theory Research**

Several recent studies have applied a profile approach to studying SDT need satisfaction (e.g., in de Wal, den Brok, Hooijer, Martens, & van den Beemt, 2014; Moran, Diefendorff, Kim, & Liu, 2012; Ratelle, Guay, Vallerand, Larose, & Senécal, 2007; Vansteenkiste, Sierens, Soenens, Luyckx, & Lens, 2009). The use of profiles characterizes a person-centered approach to the study of SDT need satisfaction. Though these new person-centered approaches may signal a paradigm shift from traditional variable-centered approaches it should not discard the findings and implications reviewed above. In fact, Marsh, Ludtke, Trautwein, and Morin (2009) suggested that person-centered approaches might complement, rather than compete with, traditional variable-centered research. As person-centered approaches may be a recent paradigm shift, readers may be less familiar with their essential details. Therefore, I will next review the fundamentals of person-centered analyses, and subsequently the results several person-centered applications using the SDT.

**Person-centered approaches.** The person-centered approach has been referred to as a “holistic, interactionistic view in which the individual is seen as an organized whole, functioning and developing as a totality” (Bergman & Magnusson, 1997, p. 291). As the focus is on the individual cases, and the relationships between cases, person-centered approaches allow for an examination of qualitatively and quantitatively different groups of individuals. In contrast, traditional variable-centered approaches focus on relations between
variables. By taking a person-centered approach, Study 1 aims to examine distinct profiles of individuals that can be defined by SDT need satisfaction. One advantage in using a person-centered approach in Study 1 is that it allows me to provide a multivariate, yet parsimonious, examination of SDT need satisfaction across all three SDT needs simultaneously. In this way, I am able, through the application of person-centered analytics, to examine discrete classifications of individuals that differ on the basis of how highly all three SDT needs are fulfilled. Critically, this method also facilitates a parsimonious investigation of change in SDT need satisfaction over time by examining transitions between profiles at Time 2 as compared to Time 1.

As my co-authors and I noted in McLarnon, Carswell, and Schneider (2015; see also O’Neill, McLarnon, Hoffart, Woodley, & Allen, in press) person-centered approaches may have several advantages as compared to traditional variable-centered analytical methods for the study of SDT need satisfaction. Traditional variable-centered approaches, like multiple regression and factor analysis, examine relationships among variables, whereas person-centered approaches, like cluster analysis or latent profile analysis (LPA), examine relationships among individuals (D. J. Bauer & Curran, 2004). Person-centered analyses identify clusters of individuals who share the same configuration or pattern of scores on a number of different variables. Individuals who share a similar pattern of scores are assigned to a specific subgroup or type based on their “profile” of scores. Inasmuch, person-centered approaches represent a more holistic view of what characterizes subgroups of individuals, such that the different configurations of mean scores within each profile reflect the combined ‘experience’ or ‘mindset’ (Meyer, Stanley, & Parfyonova, 2012) associated with varying levels of SDT need satisfaction, as the case may be. The fundamental difference is that the unit of analysis in the person-centered approach is at the level of the individual case (i.e.,
participants, teams, etc.), whereas in variable-centered approaches, the variables, or constructs they reflect, are the unit of analysis.

One of the most advanced person-centered approaches is latent profile analysis (LPA), which addresses the methodological shortcomings of other person-centered analyses. Readers may be more familiar with median split analyses and cluster analyses, both of which represent person-centered approaches, but are associated with substantial methodological limitations. Person-centered approaches, in one of its most basic forms, are represented by median (or tertiary, etc.) splits in that it compares two (or more) groups of individuals that differ on substantive and empirical grounds. However, median splits are generally not recommended given their numerous shortcomings such as loss of power and ambiguous interpretation (e.g., Cohen, 1983; Irwin, & McClelland, 2003; MacCallum, Zhang, Preacher, & Rucker, 2002). LPA is regarded as a more powerful technique, which facilitates clearer interpretation of the meaning of the groups recovered (Marsh et al., 2009; Pastor, Barron, Miller, & Davis, 2007).

Cluster analysis also represents a person-centered approach, and goes beyond a straightforward median split, and develops a classification scheme by grouping together individuals who have similar values on a set of variables, such that the within-cluster variation is minimized while the between-cluster variation is maximized (Everitt, Landau, & Leese, 2001). However, there exist few rigorous or reliable guidelines to inform researchers about the number of clusters to maintain and interpret (see Pastor et al., 2007). Furthermore, cluster analysis is predominantly seen as an exploratory technique in which the results may be difficult to compare across studies (Marsh et al. 2009; Pastor et al., 2007). LPA is advantageous as compared to cluster analysis because it is a model-based technique, which
facilitates more objective criteria to assess model-data fit (as described in more detail in Appendix A).

Furthermore, LPA is nested within the general framework of structural equation models (SEMs), and thus reflects a more flexible analytical technique than median splits, cluster analysis, or other person-centered approaches. For example, predictors of profile membership or outcomes of profile membership can be embedded in a single LPA model, which would not be possible, due to the technical constraints, in cluster analysis. As well, LPA is flexible enough to accommodate advanced statistical models that specify mediated (McLarnon, Woodley, Hoffart, & O’Neill, 2015) or moderated (O’Neill, McLarnon, Xiu, & Law, in press) pathways involving the latent profile variable. Moreover, LPAs can be explored over time, in that membership changes across timepoints can be examined. These extensions possible with LPA would not be feasible with an application of cluster analysis or median splits.

LPA represents a powerful, yet flexible analytical method that can be leveraged to investigate the presence, and nature of, subpopulations within a sample of individuals. LPA represents a subclass of analytical tools referred to as mixture models (see Magidson & Vermunt, 2004; McLachlan & Peel, 2000). Mixture refers to the notion that data may be sampled from distinct underlying populations, and thus, the observed distribution of scores represents a ‘mix’ of parameters from separate subpopulations. In contrast to SEM and CFA, which use continuous latent variables, LPA infers the presence of a categorical latent variable, of which the different categories refer to different subpopulations. The purpose of the categorical latent variable is to describe relationships between cases and account for and describe the heterogeneity of the focal indicator variables (Morin & Marsh, 2015; Nylund-Gibson, Grimm, Quirk, & Furlong, 2014).
One may be more familiar with the term \textit{latent class analysis} (LCA), which is more commonly encountered in the literature than LPA. Pastor et al. (2007) however noted that the distinction between LCA and LPA is due to the type of variable used as indicators of subpopulation membership. In LCA the indicators are of a binary or categorical nature, whereas in LPA the indicators are of a continuous nature. However, the distinction between LCA and LPA is somewhat trivial as both continuous and categorical indicators (as well as variables of a count or nominal nature) can be used in the same analysis. Moreover, the results of either LCA or LPA can, in part, be interpreted by examining the profile of mean scores (for continuous indicators) or endorsement probabilities (or thresholds for categorical indicators) across each of the estimated classifications.

Thus, regardless of what type of variable is used in LPA, or any other person-centered approach, the goal of LPA is to recover distinct groups of individuals that differ in meaningful ways. Next, I will highlight the results of several person-centered studies that have investigated profiles as defined by the SDT constructs.

\textbf{Person-centered approaches and SDT.} With a focus on the motivational outcomes of need satisfaction, Moran et al. (2012) suggested that five types of individuals, differentiated on the basis of need satisfaction, could be found in a cluster analysis. The clusters of individuals displayed differential levels of job performance and positive perceptions of one’s work environment. Furthermore, this pattern of differential outcomes supports the contention that with greater need satisfaction, improved performance and personal outcomes can result. Ratelle et al. (2007) came to a similar conclusion regarding the positive nature of groups of individuals characterized by greater need satisfaction. However, in contrast to Moran et al., Ratelle et al. only uncovered three distinct profiles of individuals. Further complicating the issue of number of profiles, Vansteenkiste et al. (2009) and in de
Wal et al. (2014) found that a four-profile solution best represented the types of people who could be differentiated on the basis of SDT need satisfaction. However, the overall results of Vansteenkiste et al. and de Wal et al. are in line with Moran et al. and Ratelle et al., and further bolster the evidence that individuals with greater need satisfaction display better adjustment and performance outcomes than individuals who are characterized by less need satisfaction. Moreover, all the above researchers noted the importance of considering SDT from a profile, or person-centered, perspective in order to gain a comprehensive understanding of SDT functioning.

Calls from Chemolli and Gagné (2014) and Gunnell and Gaudreau (2015) have also supported the continued application of person-centered approaches to the study of SDT. In particular, Chemolli and Gagné suggested that continued person-centered research would be important for gaining insight into the multidimensional structure of the SDT needs, interactions between the SDT components, and shedding new light on how SDT need satisfaction relates to various antecedents and outcomes. Gunnell and Gaudreau noted that person-centered approaches may also assist in investigating SDT from a phenomenological perspective, which may assist with developing new theoretical perspectives on the qualitative experience of various levels of need satisfaction.

Although LPA addresses several of the shortcomings of other person-centered analyses, it can still be considered an exploratory analytical tool (Marsh et al., 2009; Morin, Morizot, Boudrias, & Madore, 2011; Ram & Grimm, 2009; M. Wang & Bodner, 2007). This can be seen in the diversity of the findings offered by the studies of Moran et al., Ratelle et al., Vansteenkiste et al., and in de Wal et al. in terms of the optimal number of profiles present. Therefore to ensure confidence in the findings offered by an application of LPA, replication of a LPA solution is necessary. For example, a recent study by Gabriel, Daniels,
Diefendorff, and Greguras (2015) used a pilot study to investigate the number and nature of profiles that emerge through an application of LPA, and then sought to replicate and confirm those results with a follow-up study. Therefore, I conducted a pilot study to gain insight into the number and nature of SDT profiles present. This allowed me to approach Study 1, at least in terms of the estimation of the SDT profiles recovered at Time 1 and 2, with an eye towards confirming and cross-validating the number and type of SDT profiles that individuals may transition between over time.

The results of the pilot study, which used an independent, non-overlapping sample from that involved in Study 1, are presented in detail in Appendix B.

Following the derivation of SDT need satisfaction profile groups using LPA, given the abundance of research on the positive relation between need satisfaction and well-being (e.g., Ryan & Deci, 2000), the various profile groups should differ meaningfully on well-being. In other words, I will first seek to identify, and replicate, the number of SDT profiles, and then seek to provide evidence for the validity of the profile solution by examining the relations between the profiles and an external well-being variable. Thus, Hypothesis 1.1 is proposed to help provide evidence for the construct validity of the profile solution (see Morin & Marsh, 2015; Nylund-Gibson et al., 2014):

**Hypothesis 1.1.** Levels of well-being will differ meaningfully across the SDT need satisfaction profile groups extracted. In other words, there will be significant differences in well-being mean levels across the SDT profile groups extracted from the LPA.

**SDT Need Satisfaction During Challenging Life Transitions**

As reviewed above, the transition to a university environment from that of high school has been characterized as a profound life transition, characterized by changing responsibilities, goals, and social circles (Aquilino, 2006; Deci et al., 1991; Laursen &
Recent reports have even suggested that early semesters of one’s university career can be characterized as “falling off a cliff” (Kennedy, 2013), in that it is particularly stressful. Inasmuch, during an individual’s transition to university it is likely that changes will be observed in one’s SDT need satisfaction. However, the transition to university is unlikely to affect all individuals equally, and thus, some individuals will exhibit a change in their SDT need satisfaction, but others will have maintained their need satisfaction. Stated differently, within a longitudinal person-centered approach to SDT need satisfaction, some individuals may change profile membership (in response to the demands experienced during the transition to university), whereas others may maintain their initial profile status.

As such, the next hypothesis proposes that there are different patterns of change in SDT need satisfaction over time. There are, in fact, three possible types of transitions that may occur between need satisfaction profiles over time: individuals may transition to a worse need satisfaction profile, individuals may transition to a better need satisfaction profile, or individuals may maintain their profile membership. As reviewed previously, the predominant view in the literature is that the transition to university is a challenging and adverse experience for most individuals (e.g., Z. E. Taylor et al., 2014). Thus, I anticipate that the only profile transitions will be of individuals transitioning to a worse SDT profile, or those that have maintained their SDT status over time.

Hypothesis 1.2. There will only be two types of transitions observed in the SDT profiles across time: transitions of a downward trend, in which individuals will transition to a lower SDT profile group (“Movers”), or transitions in which individuals will maintain their membership in their initial profile group (“Stayers”).

Following from Hypothesis 1.1, for those individuals who are classified as Movers in Hypothesis 1.2 there will be a corresponding negative effect on their well-being. Inasmuch,
Movers will have significantly lower well-being than Stayers. Moreover, in line with Hypothesis 1.2, I would expect evidence of a downward trend in SDT profile membership over time as proportionally more individuals would be classified into the lower profiles after experiencing a challenging event.

**Hypothesis 1.3.** Those individuals that have demonstrated a transition between SDT need satisfaction profiles over time will have lower well-being than those individuals that have maintained their SDT need satisfaction profile membership over time.

Finally, based on the arguments and reviews of resiliency provided above, I aim to examine the dynamic nature of the WRI’s resiliency variables. Specifically, I intend to examine the conditions under which resiliency is activated, and may demonstrate its state-like nature. As suggested, the motivating force for resiliency was experiencing a substantial change in SDT need satisfaction, which could potentially have resulted from the experience of adversity. In other words, I propose that experiencing a significant change in one’s SDT need satisfaction would help explain why resiliency would be necessary.

Invoking the concepts of COR theory and the notion that resiliency is an effortful phenomenon, those individuals using their resiliency resources will actually demonstrate lower resiliency scores over time. In particular, those individuals who have experienced a downward transition in SDT profile membership will be demonstrate significantly lower resiliency scores over time, whereas those individuals that did not experience a change in SDT status will have similar levels of resiliency over time. In other words, Movers will have needed to activate their resiliency resources in order to try and restore their SDT need satisfaction and well-being (see earlier discussion; Hobfoll, 2002). However, one could conceivably argue in favor of the proposition that Stayers, in order to have maintained their need satisfaction, have employed their resiliency skills more. However, this stands in contrast
to the fundamentals of COR theory, which suggest that as an individual uses their resources to protect their well-being, the absolute level of those resources decrease. Inasmuch, Movers, not Stayers, will demonstrate a decrease in resiliency over time as they actively use their resiliency resources to restore their well-being. Stayers, on the other hand, will have consistent levels of the resiliency resources over time because they have not needed to draw upon their resources. Thus, despite both Movers and Stayers having undergone the same transition experience, Stayers will not have had to use their resiliency resources because the transition did not decrease their SDT need satisfaction. Therefore,

**Hypothesis 1.4.** Demonstrating their use of resiliency resources, SDT profile Movers will have significantly lower resiliency scores at follow-up, whereas SDT profile Stayers will have similar levels of resiliency, as defined by King and Rothstein’s (2010) eight-component resiliency model, over time.

By way of recapping the hypotheses focal to Study 1, I aim to first, apply a person-centered approach to the SDT need satisfaction variables using LPA; second, provide evidence of construct validity for the resulting LPA solution; third, examine the incidence of change in latent profile membership over time; and fourth, investigate the relation between change in SDT need satisfaction and change in resiliency over time.

**Method**

**Participants**

Participants for Study 1 were obtained from the subject pool of a large university, and participated in exchange for course credit.\(^3\) Participation in Study 1 (See Appendix C for ethics approval document) was available immediately at the opening of the subject pool for the 2014-2015 academic year.

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\(^3\) Participation in Study 1 was exclusive of participation in the pilot study, such that these two samples were independent and non-overlapping.
Participation was sought from 400 undergraduate students. The mean age for participants was 18.22 years ($SD = 1.11$), and ranged between 17 and 26. Fourteen participants did not report their age. The majority of participants identified as female (278; 67.1%), and 122 identified as male (29.5%). For the majority of participants (338; 84.3%), the Time 1 assessment occurred during their first semester of post-secondary education. 

Measures

**Self-determination theory need satisfaction.** The basic psychological need satisfaction was assessed by the Basic Needs Scale (W-BNS) from Van den Broeck et al. (2010). The W-BNS contains 18 items, six assessing each SDT need. Van den Broeck et al. reported Cronbach’s $\alpha$s of .81, .85, and .82 for the Autonomy, Competence, and Relatedness subscales, respectively. Items were adjusted slightly to remove the work focus from each. For example, one Autonomy item provide by Van den Broeck et al. was “At work, I often feel like I have to follow other people’s commands.” For the purpose of Study 1, I omitted “At work”, and asked participants to respond to “I often feel like I have to follow other people’s commands” on a five-point, Strongly disagree to Strongly agree Likert scale. The entire set of items can be found in Appendix D.

**Well-being.** A measure of overall psychological well-being from van Dierendonck (2005) was used, which is shortened version of Ryff and Keyes’ (1995; see also Ryff, 1989a, 1989b) measure. Although Ryff and Keyes’ noted that the conceptual model on which this measure is based is multidimensional, recent factor analytic evidence has shown that a single

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4 Different SDT need satisfaction measures were used between the pilot study and Study 1 in effort to reduce participant fatigue and maximize increase participant engagement over time. This is because Study 1 used a repeated measures design and with the inclusion of the resiliency measures I chose a shorter SDT measure to help keep the overall survey length as short as possible.

5 A different well-being measure was used in Study 1 as compared to the pilot study because Study 1 sought to investigate relations between SDT profiles and a general measure of well-being. The well-being construct assessed by Study 1 incorporates aspects of well-being used by the pilot study.
underlying factor accounts for the majority of variance (see Jovanović, 2015; Springer & Hauser, 2006; van Dierendonck, 2005, van Dierendonck, Díaz, Rodríguez-Carvajal, Blanco, & Moreno-Jiménez, 2008). This measure consists of 18 items. An example item includes “For me, life has been a continuous process of learning, changing, and growth.” All well-being items were responded to on a five-point Likert scale anchored by Strongly disagree and Strongly agree at the low and high endpoints, respectively. The entire set of items can be found in Appendix E.

**Psychological Capital (PsyCap).** As the PsyCap construct specifies a single, higher-order factor, and combines the functioning of Hope, Self-Efficacy, Optimism, and Resiliency the complete measure from Luthans et al. (2007) was administered. The PsyCap measure contains 24 items, with six measuring each of its facets. Previous applications of the PsyCap measure have found favorable evidence of reliability and validity (see Introduction), with Cronbach’s α of greater than .80 (see Table 2 of Dawkins et al., 2013; see also Abbas, Raja, Darr, & Bouckenooghe, 2014; Roche, Harr, & Luthans, 2014). An example item from the Resiliency subscale includes “I usually manage difficulties one way or another.” All PsyCap items were responded to on a five-point Likert scale anchored by Strongly disagree and Strongly agree at the low and high endpoints, respectively. Due to restriction on the number of items users can reproduce, five of the items comprising the PsyCap’s Resiliency scale can be located in Appendix F.

**Resiliency.** McLarnon and Rothstein’s (2013) WRI was used to assess the King and Rothstein (2010) components of resiliency. Across several diverse research contexts and studies, the WRI has demonstrated strong evidence of internal consistency reliability and criterion-related validity. For example, McLarnon and Rothstein (2013) provided compelling evidence for the moderately strong relations between the WRI facets and several measures of
well-being. Table 1 summarizes the evidence of internal consistency across the McLarnon and Rothstein study, and the studies of Kisinger (2012) and Halliday (2013), and provides example items for each of the WRI’s eight subscales.

Prior to completing the WRI, special instructions were given to each participant, which describe a priming scenario so that individuals are able to reflect on the processes associated with ‘bouncing back’ from an adverse experience (see Appendix H). A prime of this nature was effectively used by McLarnon and Rothstein (2013) in the development of the WRI. The entire set of WRI items can be found in Appendix G.

**Procedure**

At its foundation, Study 1 used a naturalistic repeated measures design with two assessment periods. As noted, participants were invited to complete a Time 1 assessment as soon as the subject pool was opened for the 2014-2015 academic year (this occurred on September 23, 2014). Invitations were then sent out for participants to complete the follow-up assessment approximately six weeks later, in the first week of November. This timeline was chosen to ensure that there was enough time between assessments to reduce carry-over effects, and also to allow for change in SDT need satisfaction during the transition to university. The follow-up measurement in November was chosen to correspond with the completion of the mid-term exam period, so that change in relation to a focused, intensive, yet naturally occurring adverse event might be assessed.

Both Time 1 and Time 2 assessments were administered using an online survey hosted by SurveyMonkey. Participants were given the link to the Time 1 survey immediately after enrolling in the study from the subject pool’s online portal. Each link was automatically customized by the online portal so that each set of responses recorded by SurveyMonkey were coded with an anonymous identification number given to each participant. Participants
were first presented with the Letter of Information, and indicated consent by clicking a ‘Next’ button and entering the survey.

In the first week of November 2014 invitations to complete the Time 2 assessment was sent out, en mass, to participants. As in the Time 1 assessment, participants were initially shown a Letter of Information. Clicking a ‘Next’ button and entering the survey, again, indicated consent. The first question participants were asked to complete in the Time 2 assessment was to provide their anonymous ID number. This was required so that Time 1 and Time 2 datasets could be matched. These ID numbers are five- or six-digit numbers automatically generated by the subject pool system and contain no personally identifying information. Participants were free to withdraw from the study at any point, and were awarded participation credits for completing both assessments. Participants were awarded .5 research credits for the initial assessment, and an additional .5 credits for the follow-up assessment, both of which are typical for a total expected study time of 45 minutes to one hour.

**Analytical Procedure**

**Latent transition analysis.** To provide an assessment of the research questions at the heart of Study 1, I used latent transition analysis (LTA; Collins, Graham, Rousculp, & Hansen, 1997; Collins & Lanza, 2010; Collins & Wugalter, 1992; Kaplan, 2008; Kam et al., in press; Reboussin, Reboussin, Liang, & Anthony, 1998; Velicer, Martins, & Collins, 1996; Vermunt, Tran, & Magidson, 2008; M. Wang & Chan, 2011). I used LTA because it allowed me to achieve a balance between parsimony and analyzing multivariate change over time.

LTA, as a longitudinal extension of LPA, can help explore the incidence and nature of transitions across latent profile membership over time (Lanza & Collins, 2010). LTA combines LPA and autoregressive modeling to identify unique classes of individuals at each
timepoint, and to additionally describe the transitions and individual-level changes that occur between profiles over time (Nylund, 2007). By modeling latent variables that are discrete or categorical in nature, LTA can examine the probability of individuals who transition from one discrete status to another over time (B. O. Muthén & Muthén, 2000; M. Wang & Hanges, 2011). LTA involves a measurement component meant to capture membership in discrete latent profiles (i.e., LPA at two or more timepoints) and a structural component that models change in latent class membership over time (i.e., transition probabilities; Nylund, Muthén, Nishina, Bellmore, & Graham, 2006). LTA allowed me to study the incidence and prevalence of different latent profiles distinguished on the basis of autonomy, relatedness, and competence need satisfaction, and how transitions across latent profiles may be related to changes in resiliency over time. The use of LTA was be informed by several recent studies that have demonstrated the LTA framework in the study of numerous psychological domains (i.e., Chung, Lanza, & Loken, 2008; Kam et al., in press; Meeus, Van de Schoot, Klimstra, & Branje, 2011; Nylund et al., 2006).

It may have been possible to consider change in SDT need satisfaction in the traditional variable-centered approach by using McArdle’s (2009) latent difference score (LDS) procedure. The LDS procedure, however, is essentially a univariate change model. This is because LDS models only consider change in one variable at a time. As such, the LDS procedure was reserved to examine change in the WRI and PsyCap covariates because its use can help overcome some of the shortcomings of difference scores (i.e., unreliability; McLarnon, O’Brien, & Rothstein, 2013; see also Eschleman, & LaHuis, 2014; McArdle, Hamagami, Chang, & Hishinuma, 2014; S. G. Taylor, Bedeian, Cole, & Zhang, in press).

The LTA was conducted in multiple steps, as recommended by Nylund (2007) and Nylund et al. (2006). The first component of this study’s analyses was an examination of the
measurement invariance (MI) of the SDT measures over time using longitudinal CFAs (LCFA). The second component explored the optimal LPA solutions of the SDT needs at each timepoint independently. Third, the LPAs were combined in a single model to assess invariance of the profile solutions. Next, using the LPA models for Time 1 and Time 2 solutions, the transitions that occur between profiles over time are examined. Last, an additional latent categorical variable was included in the combined LPA model to describe the heterogeneity of transitions. This last step includes what is referred to as a Mover-Stayer model (MS; Langeheine & van de Pol, 2002), which describes the difference between those individuals who moved membership over time and those individuals who stayed in the same profile. In general, a MS uses an additional latent categorical variable to describe and classify individuals’ transitions into discrete classes. In previous examples, a MS model has been implemented to summarize positive and negative transitions, and also separate those who have maintained their initial status (e.g., Catts, Compton, Tomblin, & Sittner-Bridges, 2012; Chung, Anthony, & Schafer, 2011; Shin, 2012; M. Wang & Chan, 2011). Based on this model, differences across the Movers and Stayers in WRI and PsyCap variables will be investigated.

**Longitudinal measurement invariance.** Any examination of change in a variable over time requires the demonstration of measurement invariance (Ployhart & Vandenberg, 2010; Vandenberg, 2002; Vandenberg & Lance, 2000). Without demonstrating MI flawed or misleading interpretations may result, as it cannot be assumed that the same construct has been measured in the same manner across time. MI is concerned with whether the variables measured at multiple time points (or across multiple groups; e.g., males versus females) function and mean the same thing (Balzer, Greguras, & Raymark, 2004). If MI is not demonstrated, any comparisons made over time (or groups) may be akin to comparing apples
to oranges (F. F. Chen & West, 2008; Geiser, Eid, Nussbeck, Courvoisier, & Cole, 2010; Marsh et al., 2011; McLarnon, 2013; Vandenberg & Lance, 2000). The investigation into MI across time points, using LCFA, assesses the stability and equivalence of a scale’s measurement model over time (e.g., Feldt, Leskinen, Kinnunen, & Ruoppila, 2003). These analyses took place before the estimation of the LPAs within a traditional CFA framework. In fact, the LPAs were based on the factor scores output from the LCFAs, as recommended by Kam et al. (in press).

MI studies can be of substantial interest in their own right (e.g., McLarnon & Carswell, 2013), but as it is only a stepping stone here, I refer readers to Millsap (2011) for additional technical details. However, I will highlight the specific steps required to demonstrate MI. First, configural invariance assesses whether the same pattern of factors and factor loadings is supported across time. Second, metric invariance assesses whether respective factor loadings are equivalent across time. To assess metric invariance, equality constraints are imposed across each factor loading from the configural invariance model. MI is supported by a non-significant change in the model $\chi^2$ value (Sass, 2011). This is because the metric invariant model is nested in the configurally invariant model (i.e., fewer parameters estimated and more degrees of freedom). As the $\Delta\chi^2$ test may be sensitive to sample size, and is often recognized to be over-powered in reasonably large samples (Brannick, 1995; Kelloway, 1995), F. F. Chen (2007), Cheung and Rensvold (2002), and Meade, Johnson, and Braddy (2008) suggested that changes in the CFI of less than .010 and/or changes in the RMSEA of less than .015 are supportive of MI. Thus, as the $\Delta\chi^2$ test may be over-powered I placed more emphasis on the $\Delta$CFI and $\Delta$RMSEA guidelines when significant $\Delta\chi^2$ values were rendered. However, when the $\Delta\chi^2$ test was not significant, I took
that as convincing evidence of invariance and do not report on the ΔCFI and ΔRMSEA estimates.

Ployhart and Vandenberg (2010) suggested that only configural and metric invariance are sufficient prior to longitudinal analyses. There are, however, several additional stages of MI one may wish to investigate to explore the cross-time (or cross-group) properties of a particular measurement tool. Building upon the equality constraints imposed for metric invariance, the strong invariance step places additional equality constraints upon the means or intercepts of the indicators (or thresholds in the case of categorical indicators). Whether MI is supported is assessed using the same guidelines for the Δχ² test, ΔCFI, and ΔRMSEA described above. Additionally, invariance of the indicator residual variances (referred to as strict invariance), latent variances (and covariances, applicable if a measurement instrument is multidimensional) and latent means can be assessed with added equality constraints and assessed using the same Δχ², ΔCFI, and ΔRMSEA guidelines. Following the procedure of Kam et al. (in press), I assessed all of these different levels of MI, but exported factor scores from the strict invariance step, which included equality constraints across the factor loadings, intercepts, and residual variances for use in the later LPAs and LTA.

Additional considerations around MI and LCFAs involve partial MI (PMI), and correlated uniquenesses (CU). PMI is when invariance of any of the model’s measurement parameters is not supported, such that a factor loading, in the metric invariance step, may not be invariant across time points (see Flora, Curran, Hussong, & Edwards, 2008). Previous researchers have provided recommendations that a measure may be considered invariant across time points, or groups, if at least metric invariance is supported for two indicators (see Byrne, Shavelson, & Muthén, 1989; Morin, Madore, Morizot, Boudrias, & Tremblay, 2009; Morin, Moullec et al., 2011; Sharma, Durvasula, & Ployhart, 2012; Vandenberg, 2002). If
any of the steps in the MI analyses surpass the $\Delta \chi^2$, $\Delta$CFI, and $\Delta$RMSEA guidelines, PMI will be investigated by releasing the equality constraint(s) found to be causing substantial misfit (see Cheung & Lau, 2012; Cheung & Rensvold, 1999; Morin, Madore et al., 2009; Raykov, Marcoulides, & Millsap, 2012).

Although not included in any of the equality constraints implemented in MI, LCFAs commonly use CUs, or autocorrelated residuals (see Ployhart & Vandenberg, 2010). Specifically, correlations between the residuals of the same indicators at separate time points will be specified. This is because with any repeated measurement there is likely some systematic variance contained in the residuals that is not due to the focal measure (see Cole & Maxwell, 2003; Jöreskog, 1979; T. D. Little, 2013; Marsh & Hau, 1996; Ployhart & Vandenberg, 2010; cf. Landis, Edwards, & Cortina, 2009). Ployhart and Vandenberg suggested that without allowing autocorrelated residuals, model fit and parameter estimates from an LCFA might be inaccurate and may lead to biased interpretations because assumption of independent residuals is unlikely to be supported.

MI analyses were conducted for each measure separately. I used the same parameterization for these LCFAs as in the pilot study (i.e., item parcels, and Little, Slegers, & Card’s [2006] non-arbitrary model identification method; see Appendix B for further details). Item parcels were used because of several advantageous properties as compared to the item-level data (see Appendix B) and the focus of these LCFAs was on the overall measurement equivalence of each construct across Time 1 and Time 2 assessment, not on the specific functioning of each item across timepoints (cf. Meade & Kroustalis, 2006).

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6 Factor loadings from the Time 1 assessments (from the configural invariance model) were used in developing the balanced item parcels (see Little, Rhemtulla, Gibson, & Schoemann, 2013; Appendix B), and parcels were constructed identically across timepoints, so that items were assigned to the same parcels at Time 2 as they were in for Time 1.
One additional concept to address regarding the LCFAs concerns the correct specification of the longitudinal null model (T. D. Little, 2013). The null model is used in the derivation of model fit indices like the CFI. The null model specifies that no covariances exist between the focal variables (i.e., factor indicators in a CFA) in the population, and only has a variance estimate. The CFI is a ratio of the \( \chi^2 \) value of a tested model to the \( \chi^2 \) of the null model. The point here is that in LCFAs, the null model is inherently incorrect (Widaman & Thompson, 2003). If the null model is incorrect, any of the CFIs used to judge model fit in MI may also be biased (recall the critical \( \Delta \text{CFI} \) of .01 to support invariance in moving from the configurally invariant model to the metric invariance model; Cheung & Rensvold, 2002).

As discussed by Widaman and Thompson (2003) and T. D. Little (2013), the correct longitudinal null model should specify that the variances of the observed variables have not changed, and that the means (intercepts, or thresholds in the case categorical indicators) should be equal over time. Thus, the correct longitudinal null model for an LCFA should specify no covariances between any indicators (as in the traditional null model), but equal variances and equal means for each respective indicator over time. Accordingly, to correctly compute the CFI for an LCFA the correct null model must first be specified. As such, the MI analyses I describe first estimated the correct longitudinal null model, and then LCFA models with increasingly strict equality constraints imposed to assess MI.

**Latent profile invariance.** As noted, following the derivation of optimal profile models from Time 1 and Time 2, the next step was to assess the invariance of the profile solutions. Similar to the longitudinal MI analyses discussed previously, profile invariance is assessed with multiple analytical steps to ensure that the same profiles emerged over time. Without demonstrating similarity across time, the transitions that occur between profiles over
time can be challenging to interpret (Nylund et al., 2006). In particular, interpretation can become ambiguous if the profile groups don’t maintain their meaning over time.

The sequence of analytical steps for testing the invariance of latent profiles is relatively new, and therefore, a thorough discussion of each step’s purpose and interpretation is reserved for Appendix I. The main point is that invariance of the Time 1 and Time 2 LPA solutions was investigated prior to combining both models for the LTA.

**Missing data.** Several strategies were used to help mitigate missing data, an inherent issue with any longitudinal research, and adhere to the best practices of statistical modeling with missing data. First, participants were informed clearly that participation in the study asked for two assessments: one immediately after signing up, and another delayed by about six weeks. When the Time 2 assessment was to be administered, invitations were sent en masse to all of the 400 individuals that had participated in the Time 1 assessment. This invitation was sent out automatically using the subject pool’s online portal. In order to maximize participation in the Time 2 assessment, three reminder emails were sent out, again using the subject pool’s online system since email addresses (or other personally identifying information) were not collected. The first reminder was sent three days after the initial invitation for Time 2 to all of the 400 participants, and the two subsequent reminders, also sent at three-day intervals, were only targeted towards those individuals that had yet to respond. A total of 338 participants provided responses to the follow-up survey after these reminder emails. This represents a response rate of 84.5% (338/400).

Second, to best leverage all data collected from participants, I conducted the LCFAs, and subsequent LPAs and LTA, using full information maximum likelihood estimation (FIML), as implemented in *Mplus* 7.31 (L. K. Muthén & Muthén, 2012, 2015) in conjunction with a robust maximum likelihood estimator (e.g., Satorra & Bentler, 1994; Yuan & Bentler,
2000; MLR in Mplus nomenclature). FIML can allow for missing data under missing completely at random (MCAR) and missing at random (MAR) assumptions (see R. J. A. Little & Rubin, 1987). FIML estimation has been found to be superior to the traditional missing data handling techniques of pairwise and listwise deletion (R. J. A. Little & Rubin, 1987; Wilkinson & APA Task Force on Statistical Inference, 1999), and has been found to result in relatively unbiased parameter estimates of longitudinal models, even in the presence of a large proportion of missing data (Enders, 2001, 2010; Enders & Bandalos, 2001; Graham, 2009, 2012; Newman, 2003, 2014). Kam et al. (in press) noted that even with 50% of data missing, FIML methods, in conjunction with MLR estimation, can provide relatively unbiased parameter estimates. This guideline is also embedded in the best practice recommendations of Enders (2010) and Graham (2009). FIML methods have also been shown to effectively estimate model parameters at par with more computationally intensive methods like multiple imputation (Larsen, 2011).

Furthermore, an important advantage of FIML methods is that the sample size will be maximized. Inasmuch, FIML methods will assist in recovering the parameters lost due to MCAR or MAR missing mechanisms. Here, the focal parameters of interest are the latent means of each measurement model. Thus, when factor scores are saved from the LCFAbs for use in the subsequent LPAs and LTA, the sample size will be maximized (i.e., \( n = 400 \)), rather than being bound by listwise deletion, which downwardly biases sample size.

The last consideration I can offer before getting to the results concerns non-purposeful responding. In the pilot study (see Appendix B) I removed participants that had not responded correctly to several items that instructed participants to select a particular option (i.e., “Please answer strongly agree to this question”). I did not embed these sorts of questions into Study 1 because I did not feel that this type of responding would be extensive.
As the measures central to the pilot study were embedded in a larger, longer online survey, non-purposeful responding was more likely to be an issue because of participant disinterest and fatigue. Participants in the pilot study may have been less interested because they simply signed up for a “Mass Testing” study, and were asked about a wide variety of attitudes and preferences. Whereas I designed Study 1 to be more engaging and gave basic background information about the Study’s measures and purpose in the Letter of Information in effort to increase the probability that participants enrolled because they were interested and motivated to respond purposefully. Additionally, I kept the surveys as short as possible (the vast majority of participants completed each survey in less than 20 minutes) to reduce participant fatigue. As such, I did not consider it necessary to exclude any participants on the basis of non-purposeful responding. As well, only a trivial portion of Time 1 respondents passed the $p < .001$ Mahalanobis distance cut-off ($n = 9; 2.25\%$), and as such all participants were retained in the sample. Thus, Study 1’s main analyses including the LCFAs and LTAs used a sample size of 400, however before proceeding to the main results, I did consider the impact that participant drop-out may have had.

**Testing drop-out effects.** To investigate the potential impact of participant drop-out, I tested systematic bias between participants who completed the Time 2 survey and those who did not. In line with the recommendations of Goodman and Blum (1996) I assessed the prevalence and potential effects of systematic, or non-random drop-out among participants with four preliminary analyses. First, I performed a logistic regression with the missing status at Time 2 as the dependent variable, and Time 1’s focal variables (PWB, SDT, WRI, and PsyCap) and the sex and age demographic variables as the predictors. Second, I examined mean differences in the Time 1 variables across respondents who responded at both timepoints, and those who only participated at Time 1 using an independent samples $t$-test.
Third, I examined differences in variances in the Time 1 variables across the whole sample of respondents and only those who responded at Time 2. Finally, I assessed whether non-random drop-out influenced the relations between the focal variables (and the demographic variables) using multiple regressions of the Time 1 data and computed separately between the full sample, and those that responded at Time 2. In these regressions, PWB was used as the dependent variable, and the SDT, WRI, PsyCap and demographic variables were used as predictors. Goodman and Blum suggested that when there are differences in results of these multiple regressions in terms of which coefficients are significant and which are not can suggest that drop-out may moderate the relations between the study variables.

Appendix J documents the results of all four of these assessments of drop-out effects (see Goodman & Blum, 1996), but in the interest of brevity only the significant effects will be highlighted. According to the logistic regression, the only variable that significantly contributed to the prediction of missing at Time 2 was the WRI’s PCC component ($b = -.703$, $p < .005$, odds ratio [OR] = .495). Thus, with increasing levels of Time 1 PCC, participants were more likely to have dropped-out for Time 2. This corresponded with a significant mean difference as signaled by the independent samples $t$-test, $t(398) = 2.757$, $p < .005$. In the third test, no variables, including PCC, were found to have variances that differed significantly across all individuals who responded at Time 1 and those that only responded at Time 2. As for the multiple regression analyses, there was only a difference in significance for the relations involving age, in which it was non-significant in the regression for the whole sample, but was significant in the regression using data from only those who responded at Time 2. However, the difference between the numeric value in these regression coefficients was not found to be significant (see Goodman & Blum, 1996; Kenny, 1987). Based on this
limited evidence for the systematic effects of participants who did not respond to the Time 2 survey, the implications associated with these will only be discussed further in the Discussion.

**Results**

Descriptive statistics and intercorrelations for Study 1’s Time 1 and Time 2 focal variables can be found in Table 2. Table 3 presents the Cronbach’s α and test-retest reliability estimates.

**Longitudinal Confirmatory Factor Analyses**

Although I discussed MI, and the need for demonstrating MI above, the results of the LCFAs used to support the longitudinal validity and MI of the SDT, PWB, PsyCap, and WRI measures across timepoints is more of a stepping-stone before estimating the LPAs and LTA focal to Study 1. Thus, although the results of LCFAs and MI analyses can be interesting in their own right, they are not the focus of this dissertation. As such, the details and Tables supporting the LCFA results are presented in Appendix K.

The takeaway message is that the measures pertinent to this study demonstrated strict invariance over time. In other words, the LCFAs conducted on Study 1’s measures supports the longitudinal validity of each measure. Supporting the MI and longitudinal validity of each measure suggests that each functions and means the same to respondents across timepoints (Chan, 2011).

**Latent Profile Analysis, Time 1**

Appendix B described the LPA technical details used in the pilot study, which were replicated for Study 1.
Table 2

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<td>.047</td>
<td>-.288</td>
<td>.180</td>
<td>.235</td>
<td>.323</td>
</tr>
<tr>
<td>9 OSR</td>
<td>.353</td>
<td>.306</td>
<td>.406</td>
<td>.469</td>
<td>.374</td>
<td>.114</td>
<td>.258</td>
<td>.027</td>
<td>--</td>
<td>-.196</td>
<td>.134</td>
<td>.043</td>
<td>.303</td>
</tr>
<tr>
<td>10 IR</td>
<td>-.506</td>
<td>-.392</td>
<td>-.446</td>
<td>-.422</td>
<td>-.483</td>
<td>-.394</td>
<td>-.152</td>
<td>-.204</td>
<td>-.192</td>
<td>--</td>
<td>-.171</td>
<td>-.209</td>
<td>-.530</td>
</tr>
<tr>
<td>11 SRP-A</td>
<td>.230</td>
<td>.217</td>
<td>.015</td>
<td>.235</td>
<td>.271</td>
<td>.262</td>
<td>.284</td>
<td>.200</td>
<td>.067</td>
<td>-.154</td>
<td>--</td>
<td>.375</td>
<td>.171</td>
</tr>
<tr>
<td>12 SRP-B</td>
<td>.248</td>
<td>.336</td>
<td>.008</td>
<td>.307</td>
<td>.271</td>
<td>.195</td>
<td>.475</td>
<td>.188</td>
<td>.142</td>
<td>-.139</td>
<td>.416</td>
<td>--</td>
<td>.484</td>
</tr>
<tr>
<td>13 SRP-C</td>
<td>.529</td>
<td>.524</td>
<td>.439</td>
<td>.557</td>
<td>.675</td>
<td>.512</td>
<td>.299</td>
<td>.300</td>
<td>.347</td>
<td>-.510</td>
<td>.203</td>
<td>.308</td>
<td>--</td>
</tr>
</tbody>
</table>

**T1 Mean**

|----------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|

**T1 SD**

|          | .588  | .652  | .834  | .407  | .477  | .715  | .534  | .668  | .818  | .690  | .663  | .662  | .710  |

**T2 Mean**

|----------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|

**T2 SD**

|          | .577  | .624  | .810  | .431  | .514  | .717  | .586  | .725  | .734  | .672  | .653  | .652  | .704  |

*Note.* Correlations for the Time 1 assessments are below the diagonal, and correlations for the Time 2 assessments are above the diagonal. \( n = 400 \) for Time 1, \( n = 322 \) for Time 2. For Time 1 correlations greater than \(|.10|, p < .05\), greater than \(|.13|, p < .01\). For Time 2 correlations greater than \(|.11|, p < .05\), greater than \(|.15|, p < .01\). SDT-A = self-determination theory – autonomy; SDT-C = self-determination theory – competence; SDT-R = self-determination theory – relatedness; PWB = psychological well-being; PC-A = Personal Characteristics – Affective; PC-B = Personal Characteristics – Behavioral; PC-C = Personal Characteristics – Cognitive; IR = Initial Response; OSR = Opportunities, Supports, and Resources; SRP-A = Self-Regulatory Processes – Affective; SRP-B = Self-Regulatory Processes – Behavioral; SRP-C = Self-Regulatory Processes – Cognitive.
Table 3

*Study 1 Reliability*

<table>
<thead>
<tr>
<th>Scale</th>
<th>Cronbach’s α</th>
<th>Test-Retest</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Time 1</td>
<td>Time 2</td>
</tr>
<tr>
<td><strong>Self-Determination Theory</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Autonomy</td>
<td>.633</td>
<td>.672</td>
</tr>
<tr>
<td>Competence</td>
<td>.754</td>
<td>.710</td>
</tr>
<tr>
<td>Relatedness</td>
<td>.836</td>
<td>.844</td>
</tr>
<tr>
<td><strong>Psychological Well-Being</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>.757</td>
<td>.807</td>
</tr>
<tr>
<td><strong>PsyCap</strong></td>
<td>.878</td>
<td>.896</td>
</tr>
<tr>
<td><strong>WRI</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PC-A</td>
<td>.833</td>
<td>.853</td>
</tr>
<tr>
<td>PC-B</td>
<td>.830</td>
<td>.851</td>
</tr>
<tr>
<td>PC-C</td>
<td>.778</td>
<td>.822</td>
</tr>
<tr>
<td>OSR</td>
<td>.958</td>
<td>.962</td>
</tr>
<tr>
<td>IR</td>
<td>.795</td>
<td>.782</td>
</tr>
<tr>
<td>SRP-A</td>
<td>.795</td>
<td>.793</td>
</tr>
<tr>
<td>SRP-B</td>
<td>.793</td>
<td>.793</td>
</tr>
<tr>
<td>SRP-C</td>
<td>.843</td>
<td>.840</td>
</tr>
</tbody>
</table>

*Note.* All test-retest reliability coefficients significant at $p < .01$. 

All Time 1 LPAs converged on well-replicated solutions, in that the best loglikelihood was found from a large proportion of the second-stage starting values. This would suggest that for each of the profile models estimated a true global solution was reached. Table 4 provides the model fit indices for the Time 1 LPAs. Whereas the models with one to four profiles extracted elicited no warnings from *Mplus*, in the five-profile model one of the profiles was estimated to have a near-zero variance of relatedness. This would suggest that out of the five models estimated, only those models with one to four profiles were statistically appropriate. This issue was likely due to low profile size, in that a very small proportion of individuals were assigned to this group (*n* = 6; 1.5%) in the five-profile model. This suggests inferiority of the five-profile solution as compared to alternative models with fewer profiles.

Table 4 also shows that the entropy values, which reflect classification accuracy (see Appendix A), were generally acceptable across the profile models. Entropy increased slightly with increasing the number of profiles extracted, suggesting that individuals could increasingly be accurately classified into profile groups as the number of profiles extracted increased. Aside from the five-profile model, each profile grouping accounted for a reasonably large proportion of individuals, in that each profile contained more than 5% of the total cases (see Table 5).

In keeping with Morin and Marsh’s (2015) recommendations, I examined the information criteria values by way of an elbow plot (Figure 2). As noted in Appendix A, this can assist with determining an optimal LPA model because strictly relying on the point at which the information criteria are at a minimum can lead to extracting spurious profiles. The elbow appears to occur with the three-profile model, suggesting the improvement in fit with the four-profile model was trivial.
Table 4

Latent Profile Analyses Results – Study 1, Time 1

<table>
<thead>
<tr>
<th># Profiles</th>
<th>LL</th>
<th>LLc</th>
<th>#fp</th>
<th>AIC</th>
<th>CAIC</th>
<th>BIC</th>
<th>aBIC</th>
<th>Entropy</th>
<th>aLMR</th>
<th>BLRT</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-956.442</td>
<td>1.008</td>
<td>6</td>
<td>1924.884</td>
<td>1934.502</td>
<td>1948.848</td>
<td>1929.810</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>2</td>
<td>-782.169</td>
<td>1.202</td>
<td>13</td>
<td>1590.338</td>
<td>1611.179</td>
<td>1642.260</td>
<td>1601.01</td>
<td>.756</td>
<td>.000</td>
<td>.000</td>
</tr>
<tr>
<td>3</td>
<td>-712.151</td>
<td>1.130</td>
<td>20</td>
<td>1464.301</td>
<td>1496.365</td>
<td>1544.180</td>
<td>1480.719</td>
<td>.770</td>
<td>.000</td>
<td>.000</td>
</tr>
<tr>
<td>4</td>
<td>-673.314</td>
<td>1.030</td>
<td>27</td>
<td>1400.628</td>
<td>1443.913</td>
<td>1508.465</td>
<td>1422.792</td>
<td>.825</td>
<td>.001</td>
<td>.000</td>
</tr>
<tr>
<td>5</td>
<td>-652.595</td>
<td>1.057</td>
<td>34</td>
<td>1373.19</td>
<td>1427.697</td>
<td>1508.985</td>
<td>1401.100</td>
<td>.849</td>
<td>.185</td>
<td>.000</td>
</tr>
</tbody>
</table>

*Note.* LL = model loglikelihood; LLc = scaling correction factor for loglikelihood; #fp = number of parameters estimated in each model; AIC = Akaike Information Criterion; CAIC = Consistent AIC; BIC = Bayesian Information Criterion; aBIC = sample-size adjusted BIC; Entropy = index of classification quality; aLMR = adjusted Lo-Mendell-Rubin test *p*-value; BLRT = bootstrapped likelihood ratio test *p*-value.
I also considered the results provided by the aLMR and BLRT, which are also provided in Table 4. As in the information criteria, these results suggested that model fit was continually improved with additional profiles. Again, drawing from Morin and Marsh (2015), these statistics may fail to conclusively indicate a best fitting model because they are sensitive to sample size. This should not diminish the utility of the aLMR and BLRT estimates, but highlights the need to weigh evidence from multiple indicators of fit when determining an optimal solution in LPA (see Goffin, 2007; Marsh, Hau, & Wen, 2004; Marsh, Hau, & Grayson, 2005 for similar discussions of fit in CFA). To this end, the aLMR and BLRT results suggested that the two-profile solution represented a significant improvement in fit over and above a single profile model (\(p < .001\)). Likewise, in comparing the three- to the two-profile model (or the four- to the three-profile model) the aLMR and BLRT results suggested that the successive models fit significantly better (\(p < .001\)). Thus, as the five-profile model was not supportable due to its statistical inadequacy, models up to the four-profile model demonstrated continually improving fit with additional profiles.

Based on these indicators of fit, the three-profile model was deemed optimal. The three-profile model demonstrated a significant improvement in fit (aLMR and BLRT \(p < .001\)), and substantially smaller information criteria values over the two-profile model. Moreover, the three-profile solution is more parsimonious for two reasons. As indicated by the elbow plot, the improvement in fit of the four-profile model as compared to the three-profile solution was trivial. Additionally, the four-profile solution recovered a profile that had somewhat sparse membership (i.e., \(n = 24; 6.0\%\)). Thus, I concluded that the optimal LPA model for Time 1 was that of the three-profile solution.
Table 5

*Membership Proportions for the Study 1, Time 1 Latent Profile Analyses*

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-Profile</td>
<td>100%</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2-Profile</td>
<td>31.67%</td>
<td>68.33%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3-Profile</td>
<td>19.20%</td>
<td>45.89%</td>
<td>34.91%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4-Profile</td>
<td>18.45%</td>
<td>36.66%</td>
<td>38.90%</td>
<td>6.00%</td>
<td></td>
</tr>
<tr>
<td>5-Profile</td>
<td>18.45%</td>
<td>1.50%</td>
<td>33.42%</td>
<td>40.90%</td>
<td>5.74%</td>
</tr>
</tbody>
</table>

*Note. n = 400. Table denotes proportion of cases assigned to each profile in each of the profile models.*
Figure 2. Elbow plot of Study 1, Time 1 LPA information criteria values. AIC = Akaike information criteria; CAIC = consistent AIC; BIC = Bayesian information criteria; aBIC = sample-size adjusted BIC.
After deriving an optimal LPA solution, the next step is to interpret the profiles that have emerged in this solution. Thus, I examined the means of the SDT variables across the profiles of the three-profile solution. Table 6 and Figure 3 presents the mean levels of the three SDT variables across the optimal three-profile solution. As in the three-profile solution recovered from the pilot study, the three profiles are differentiated primarily on the basis of level. One profile has relatively low levels of autonomy, competence, and relatedness need satisfaction. Moderate SDT need satisfaction levels characterize the second profile, and the final group has comparatively higher scores on all three SDT need satisfaction variables. Moreover, I assessed mean differences in autonomy, competence, and relatedness across the three profiles using the multivariate delta method (Raykov & Marcoulides, 2004) and Mplus’ MODEL CONSTRAINT command. All autonomy, competence, and relatedness means differed significantly across the three profiles (ps < .001). These profile groups were therefore referred to as Low, Moderate, and High, respectively. Thus, the number and nature of SDT profiles is replicated across the pilot study and Study 1, providing evidence of cross-validation of the three-profile solution.

Finally, to help provide evidence of construct validity of the three-profile solution, mean differences of the PWB variable were examined across the Low, Moderate, and High profiles using Mplus’ AUXILIARY command (see Appendix B). Table 7 provides evidence of significantly different PWB across all three SDT profiles. Thus, the High profile does indeed have significantly greater well-being than the Moderate and Low profile groups, and that the Moderate group has higher well-being than the Low group. Therefore, Hypothesis 1.1 received support. For the sake of completion, Table 7 additionally presents the means of the Time 1 WRI and PsyCap variables across the three profiles, however interpretation of the relation between the profiles and resiliency is reserved until the LTA.
Table 6

Mean SDT Need Satisfaction for Study 1, Time 1’s Three-Profile Solution

<table>
<thead>
<tr>
<th>Profile</th>
<th>Autonomy</th>
<th>Competence</th>
<th>Relatedness</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>3.009</td>
<td>3.071</td>
<td>2.778</td>
</tr>
<tr>
<td>Moderate</td>
<td>3.574</td>
<td>3.613</td>
<td>3.580</td>
</tr>
<tr>
<td>High</td>
<td>4.036</td>
<td>4.015</td>
<td>4.196</td>
</tr>
</tbody>
</table>

Note. All autonomy, competence, and relatedness means differ significantly across the three profiles at $p < .001$. 
Figure 3. Profile of SDT means for Study 1, Time 1’s three-profile solution.
Latent Profile Analysis, Time 2

As in the Time 1 LPAs, the indicator variables used in the Time 2 LPAs were the latent factor scores derived from the strict invariance analysis of the SDT measure that included the factor loading, parcel means, and residual variance equality constraints. Also in keeping with the Time 1 LPAs, the Time 2 LPAs were estimated with identical technical specifications.

All Time 2 LPAs converged on solutions that reflected global solutions, in that the best loglikelihood estimates reported resulted from a large proportion of the second-stage iterations. Table 8 provides the model fit indices for the Time 2 LPAs that extracted one to five profiles. All five models converged on statistically admissible solutions (i.e., without negative variance estimates). Similar to Time 1, entropy was also quite high regardless of the number of profiles extracted, suggesting reasonably good classification accuracy. However, both the four- and five-profile models recovered profiles with a marginal, and potentially trivial, proportion of membership (see Table 9). In particular, only 25 (6.23%) cases were assigned to one of the profiles in the four-profile solution, and in the five-profile solution one of the resulting profiles contained only 5.74% of the individuals (n = 23). Thus, based on membership size, the four- and five-profile solutions may be suspect.

Similar to the Time 1 results, the information criteria values continually decreased with increasing number of profiles extracted. Figure 4 presents the plot of Time 2’s information criteria values. As in the previous results, the elbow appears to correspond with the three-profile solution, suggesting that the improvement in model fit offered by the four-profile solution is trivial.
### Table 7

**Study 1, Time 1 Wald Test of Equality of PWB and Resiliency Means Across the Three Profile Solution**

<table>
<thead>
<tr>
<th></th>
<th>Low</th>
<th>Moderate</th>
<th>High</th>
<th>Overall $\chi^2(2)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>PWB</td>
<td>3.362&lt;sub&gt;a&lt;/sub&gt;</td>
<td>3.740&lt;sub&gt;b&lt;/sub&gt;</td>
<td>4.105&lt;sub&gt;c&lt;/sub&gt;</td>
<td>190.167*</td>
</tr>
<tr>
<td>PC-A</td>
<td>2.628&lt;sub&gt;a&lt;/sub&gt;</td>
<td>3.065&lt;sub&gt;b&lt;/sub&gt;</td>
<td>3.358&lt;sub&gt;c&lt;/sub&gt;</td>
<td>43.980*</td>
</tr>
<tr>
<td>PC-B</td>
<td>3.630&lt;sub&gt;a&lt;/sub&gt;</td>
<td>3.835&lt;sub&gt;a&lt;/sub&gt;</td>
<td>4.205&lt;sub&gt;b&lt;/sub&gt;</td>
<td>59.386*</td>
</tr>
<tr>
<td>PC-C</td>
<td>3.069&lt;sub&gt;a&lt;/sub&gt;</td>
<td>3.243&lt;sub&gt;a&lt;/sub&gt;</td>
<td>3.579&lt;sub&gt;b&lt;/sub&gt;</td>
<td>29.001*</td>
</tr>
<tr>
<td>IR</td>
<td>3.298&lt;sub&gt;a&lt;/sub&gt;</td>
<td>2.731&lt;sub&gt;b&lt;/sub&gt;</td>
<td>2.208&lt;sub&gt;c&lt;/sub&gt;</td>
<td>129.299*</td>
</tr>
<tr>
<td>OSR</td>
<td>3.627&lt;sub&gt;a&lt;/sub&gt;</td>
<td>4.438&lt;sub&gt;b&lt;/sub&gt;</td>
<td>4.643&lt;sub&gt;b&lt;/sub&gt;</td>
<td>52.259*</td>
</tr>
<tr>
<td>SRP-A</td>
<td>3.184&lt;sub&gt;a&lt;/sub&gt;</td>
<td>3.316&lt;sub&gt;a,b&lt;/sub&gt;</td>
<td>3.559&lt;sub&gt;b&lt;/sub&gt;</td>
<td>15.504*</td>
</tr>
<tr>
<td>SRP-B</td>
<td>2.862&lt;sub&gt;a&lt;/sub&gt;</td>
<td>3.047&lt;sub&gt;a,b&lt;/sub&gt;</td>
<td>3.258&lt;sub&gt;b&lt;/sub&gt;</td>
<td>14.839*</td>
</tr>
<tr>
<td>SRP-C</td>
<td>2.327&lt;sub&gt;a&lt;/sub&gt;</td>
<td>3.036&lt;sub&gt;b&lt;/sub&gt;</td>
<td>3.552&lt;sub&gt;c&lt;/sub&gt;</td>
<td>185.054*</td>
</tr>
<tr>
<td>PsyCap</td>
<td>3.010&lt;sub&gt;a&lt;/sub&gt;</td>
<td>3.495&lt;sub&gt;b&lt;/sub&gt;</td>
<td>3.874&lt;sub&gt;c&lt;/sub&gt;</td>
<td>181.823*</td>
</tr>
</tbody>
</table>

**Notes.** Different subscripts differ at $p < .001$. PWB = psychological well-being; PC-A = Personal Characteristics – Affective; PC-B = Personal Characteristics – Behavioral; PC-C = Personal Characteristics – Cognitive; IR = Initial Response; OSR = Opportunities, Supports, and Resources; SRP-A = Self-Regulatory Processes – Affective; SRP-B = Self-Regulatory Processes – Behavioral; SRP-C = Self-Regulatory Processes – Cognitive; Overall $\chi^2 = $ global $\chi^2$ test, with $df = 2$, for the equality of means across all three profile groups. * $p < .001$. 

---

**RESILIENCY AND WELL-BEING**

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*67*
Table 8

*Latent Profile Analyses Results – Study 1, Time 2*

<table>
<thead>
<tr>
<th># Profiles</th>
<th>LL</th>
<th>LLc</th>
<th>#fp</th>
<th>AIC</th>
<th>CAIC</th>
<th>BIC</th>
<th>aBIC</th>
<th>Entropy</th>
<th>aLMR</th>
<th>BLRT</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-882.350</td>
<td>1.025</td>
<td>6</td>
<td>1776.699</td>
<td>1786.319</td>
<td>1800.663</td>
<td>1781.625</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>2</td>
<td>-672.650</td>
<td>1.152</td>
<td>13</td>
<td>1371.301</td>
<td>1392.141</td>
<td>1423.222</td>
<td>1381.972</td>
<td>.822</td>
<td>.000</td>
<td>.000</td>
</tr>
<tr>
<td>3</td>
<td>-599.476</td>
<td>1.200</td>
<td>20</td>
<td>1238.952</td>
<td>1271.015</td>
<td>1318.831</td>
<td>1255.369</td>
<td>.870</td>
<td>.006</td>
<td>.000</td>
</tr>
<tr>
<td>4</td>
<td>-532.792</td>
<td>1.839</td>
<td>27</td>
<td>1119.584</td>
<td>1162.869</td>
<td>1227.421</td>
<td>1141.748</td>
<td>.878</td>
<td>.005</td>
<td>.000</td>
</tr>
<tr>
<td>5</td>
<td>-502.722</td>
<td>1.311</td>
<td>34</td>
<td>1073.444</td>
<td>1127.914</td>
<td>1209.238</td>
<td>1101.354</td>
<td>.882</td>
<td>.387</td>
<td>.000</td>
</tr>
</tbody>
</table>

*Note.* LL = model loglikelihood; LLc = scaling correction factor for loglikelihood; #fp = number of parameters estimated in each model; AIC = Akaike Information Criterion; CAIC = Consistent AIC; BIC = Bayesian Information Criterion; aBIC = sample-size adjusted BIC; Entropy = index of classification quality; aLMR = adjusted Lo-Mendell-Rubin test *p*-value; BLRT = bootstrapped likelihood ratio test *p*-value.
Table 9

*Membership Proportions for the Study 1, Time 2 Latent Profile Analyses*

<table>
<thead>
<tr>
<th>Profile</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-Profile</td>
<td>100%</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2-Profile</td>
<td>48.34%</td>
<td>51.62%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3-Profile</td>
<td>50.62%</td>
<td>38.15%</td>
<td>11.22%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4-Profile</td>
<td>6.23%</td>
<td>11.72%</td>
<td>36.91%</td>
<td>45.14%</td>
<td></td>
</tr>
<tr>
<td>5-Profile</td>
<td>5.74%</td>
<td>15.71%</td>
<td>38.65%</td>
<td>10.97%</td>
<td>28.68%</td>
</tr>
</tbody>
</table>

*Note. n = 400. Table denotes proportion of cases assigned to each profile in each of the profile models.*
The fit indices offered by the aLMR and BLRT in Table 8 also mimic the Time 1 results (see Table 4). Generally, both the aLMR and BLRT suggested that increasing the number of profiles to extract led to a significant improvement in model-data fit. However, the aLMR suggested that the five-profile solution versus the four-profile was not a significant improvement in fit. Thus, profile models with increasing numbers of profiles extracted demonstrate improved model-data correspondence.

Taken together, however, these indicators of fit also suggest that the three-profile model is optimal. This was primarily determined by an examination of the elbow plot of information criteria values, which suggested that the improvement in fit of the four-profile model over the three-profile model was trivial. Based on these results, I concluded that a three-profile solution is optimal for the Time 2 LPAs.

Table 10 and Figure 5 presents the mean levels of the three SDT variables assessed at Time 2 across the three-profile solution. As in the two previous investigations, the profiles are largely differentiated on the basis of level. Comparing Figures 2 and 5 suggests a high degree of similarity. The Time 2 three-profile reflects all three of the profiles recovered by the Time 1 LPA. As such, I used the same labels for each of the profile groups recovered at Time 2: Low, Moderate, and High. I also assessed mean differences of autonomy, competence, and relatedness across the three profiles using the multivariate delta method (Raykov & Marcoulides, 2004) described earlier. All autonomy, competence, and relatedness means differed significantly across all three profiles ($p < .001$). Therefore, the Time 2 profiles provide strong evidence of replicating the profile structure recovered from the pilot study and Time 1.
Figure 4. Elbow plot of Study 1, Time 2 LPA information criteria values. AIC = Akaike information criteria; CAIC = consistent AIC; BIC = Bayesian information criteria; aBIC = sample-size adjusted BIC.
Table 10

*Mean SDT Values for Study 1, Time 2’s Three-Profile Solution*

<table>
<thead>
<tr>
<th>Profile</th>
<th>Autonomy</th>
<th>Competence</th>
<th>Relatedness</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>3.227</td>
<td>3.288</td>
<td>3.199</td>
</tr>
<tr>
<td>Moderate</td>
<td>3.777</td>
<td>3.740</td>
<td>4.091</td>
</tr>
<tr>
<td>High</td>
<td>4.168</td>
<td>4.226</td>
<td>4.288</td>
</tr>
</tbody>
</table>

*Note.* All autonomy, competence, and relatedness means differ significantly across the three profiles at $p < .001$. 
Figure 5. Profile of SDT means for Study 1, Time 2’s three-profile solution.
Incorporating Time 2’s well-being measure, as a means to provide evidence for the construct validity of the profiles recovered at Time 2, also demonstrates meaningful differences across the profiles. Table 11 provides evidence of significantly different PWB across the three Time 2 profiles. Specifically, High has significantly greater PWB than both the Low and Moderate profiles. Likewise, Moderate has significantly greater PWB than those individuals in the Low group. Thus, Hypothesis 1.1 obtained additional support from the Time 2 analyses. Table 11 also presents the means of the Time 2 assessments of the WRI and PsyCap variables across the three profiles for the sake of completion, but interpretation of the relation between the profiles and resiliency is reserved till the LTA.

**Measurement Invariance of Latent Profile Analysis Solutions**

The next step in Study 1 was to combine the LPA models from Time 1 and Time 2. Similar to the LCFA-based tests of invariance discussed earlier, this combined model was used to investigate the invariance of the profile solutions from both timepoints to ensure comparability across time. As the procedure, and thoroughly demonstrated applications, of latent profile invariance is a relatively new addition to the methodological literature (Nylund, 2007; Nylund et al., 2006; cf. Eid, Langeheine, & Deiner, 2003; Geiser, Lehmann, & Eid, 2006; Hoferichter, Raufelder, Eid, & Bukowski, 2014; Morin, Meyer, Creusier, & Biétry, 2016), but still more of a necessary precondition, rather than a focal set of results, I have detailed the findings in Appendix L, and only provide a summary below.

The takeaway message is that the SDT profiles focal to this study demonstrate substantial evidence of invariance over time. In other words, the combined LPA models conducted on the SDT profiles recovered at Time 1 and Time 2 supports the longitudinal validity of the profile solution. Supporting the longitudinal validity of the profile solution suggests that the same profiles have emerged over time, which facilitates direct comparisons
### Table 11

*Study 1, Time 2 Wald Test of Equality of PWB and Resiliency Means Across Profiles*

<table>
<thead>
<tr>
<th></th>
<th>Low</th>
<th>Moderate</th>
<th>High</th>
<th>Overall $\chi^2(2)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>PWB</td>
<td>3.435a</td>
<td>3.883b</td>
<td>4.153c</td>
<td>169.094*</td>
</tr>
<tr>
<td>PC-A</td>
<td>2.830a</td>
<td>3.226b</td>
<td>3.431b</td>
<td>31.974*</td>
</tr>
<tr>
<td>PC-B</td>
<td>3.557a</td>
<td>3.924b</td>
<td>4.371c</td>
<td>94.080*</td>
</tr>
<tr>
<td>PC-C</td>
<td>3.018a</td>
<td>3.357b</td>
<td>3.588b</td>
<td>26.231*</td>
</tr>
<tr>
<td>IR</td>
<td>3.064a</td>
<td>2.522b</td>
<td>2.098c</td>
<td>104.920*</td>
</tr>
<tr>
<td>OSR</td>
<td>4.163a</td>
<td>4.586b</td>
<td>4.766c</td>
<td>39.390*</td>
</tr>
<tr>
<td>SRP-A</td>
<td>3.295a</td>
<td>3.406a</td>
<td>3.667a</td>
<td>10.264</td>
</tr>
<tr>
<td>SRP-B</td>
<td>2.868a</td>
<td>3.044a</td>
<td>3.455b</td>
<td>25.672*</td>
</tr>
<tr>
<td>SRP-C</td>
<td>2.600a</td>
<td>3.164b</td>
<td>3.719c</td>
<td>118.078*</td>
</tr>
<tr>
<td>PsyCap</td>
<td>3.244a</td>
<td>3.695b</td>
<td>3.939b</td>
<td>97.833*</td>
</tr>
</tbody>
</table>

*Notes. Different subscripts differ at $p < .001$. PWB = psychological well-being; PC-A = Personal Characteristics – Affective; PC-B = Personal Characteristics – Behavioral; PC-C = Personal Characteristics – Cognitive; IR = Initial Response; OSR = Opportunities, Supports, and Resources; SRP-A = Self-Regulatory Processes – Affective; SRP-B = Self-Regulatory Processes – Behavioral; SRP-C = Self-Regulatory Processes – Cognitive. Overall $\chi^2 = \text{global } \chi^2$ test, with $df = 2$, for the equality of means across all three profile groups. * $p < .001.$*
between profiles over time, and straight-forward interpretation of any transitions that may be observed over time (Nylund, 2007).

As noted by Morin et al. (2016) there are four major (configural, structural, dispersive, and distributional) analytical steps to demonstrating invariance of a profile solution. However, although Morin et al. noted these four steps, they also suggested that by at least demonstrating configural and structural invariance across LPA models subsequent analyses are facilitated. Notably, configural invariance (same number of profiles), structural invariance (same means of profile indicators), and dispersive invariance (equal variances of profile indicators) was supported by the three SDT profiles recovered in Time 1 and Time 2. On the other hand, distributional invariance (equal proportion of the sample in each profile group) could not be supported. Inasmuch, the membership size of the profiles differs over time, and to be expanded upon subsequently, it appears that there was a significant downward trend in membership over time.

**Cross-Sectional Transitions**

Based on the recommendations of Nylund (2007) and Nylund et al. (2006), after demonstrating invariance of the LPA solutions, I then examined cross-sectional transition probabilities. To do this, Mplus provided the most likely profile each case was a member of at each timepoint. I then compiled a summary of each individual’s membership at Time 1, and subsequent membership at Time 2. Table 12 presents this summary, and the transitions observed in the current study.

One particularly interesting finding is that although nearly 35% of the sample was classified as being a member of the High profile at Time 1, only 11% of the sample remained in that profile at Time 2. This is remarkable, given the amount of evidence presented by the LCFA and LPA invariance analyses. Inasmuch, the events experienced between the first
assessment and the second were challenging enough that over 50% of the sample transitioned downwardly into a worse profile (i.e., lower SDT need satisfaction).

Although there was a substantial amount of change from the High profile down to the Moderate profile, there were no individuals that, given their initial membership in the High profile, transitioned to the Low profile. In fact, there was some degree of consistency across time. Again, referring to Table 12, in particular the diagonal proportions presented, suggests that between 11% and 19% of the sample maintained their profile status over time. 11.22%, initially classified as a member of High, exhibited High profile membership at Time 2. Likewise, 15.71% of the sample that were Moderate at Time 1 was also Moderate at Time 2. The Low class, which had the smallest membership at Time 1 \((n = 77, 19.20\%)\), was extremely consistent. As noted, no individual classified as a member of the Low profile at Time 1 transitioned out of the Low profile.

These transitions make one finding clear: there were no positive transitions over time. In other words, each participant’s initial status determined which profile he or she could transition into. If you were in the Moderate profile you could only be a member of the Moderate profile or the Low profile at follow-up. If you were in the Moderate profile at Time 1 there was a zero probability that an individual would be in the High profile at the follow-up assessment. The next steps of the current research then focus on separating those who transitioned and those who didn’t over time, and exploring relations with resiliency.

**Latent Transition Analysis**

Readers are directed to Appendix M for technical aspects on two analytical details I needed to address when conducting the LTA.
Table 12

*Cross-Sectional Transition Probabilities*

<table>
<thead>
<tr>
<th>Time 1</th>
<th>Low</th>
<th>Moderate</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>19.20%</td>
<td>--</td>
<td>-- a</td>
</tr>
<tr>
<td>Time 2</td>
<td>31.67%</td>
<td>15.71%</td>
<td>-- a</td>
</tr>
<tr>
<td>High</td>
<td>-- a</td>
<td>22.19%</td>
<td>11.22%</td>
</tr>
</tbody>
</table>

*Note.* $n = 400.$ Presented are proportions of sample achieving membership at Time 2, as compared to their Time 1 status. Nylund-Gibson et al.’s (2014) three-step procedure for controlling for imperfect profile membership used in computation of transitions. *a* Indicates empty transitions (i.e., no participants that were a member of the Low profile at Time 1 transitioned to the Moderate or High profiles at Time 2).
Similar to LPA, there are no absolute estimates of model-data fit (i.e., no CFI or RMSEA) for LTA. I did, however, compare the fit of the LTA to a model in which all of the transition probabilities were fixed to zero to demonstrate the superior fit of a model, in which the transitions described above were freely estimated. The model with the transitions fit the data significantly better, $\Delta \chi^2(3) = 1,159.834, p < .001$, and demonstrated lower information criteria (AIC = 1,391.964 vs. 2,545.528, BIC = 1,411.664 vs. 2,553.516, aBIC = 1,395.798 vs. 2,547.179). The proportion of transitions resulting from this LTA reflects those depicted in Table 12, so they are not replicated here. However, what is notable here is that these transitions are supported using methodology that can help account for imperfect classification accuracy (see Appendix M for further details). This analysis supports the finding that membership in SDT profiles is prone to instability over time. In particular, 53.86% of the sample underwent a transition, such that their Time 2 profile was different than their Time 1 profile. Conversely, this suggests that 46.13% maintain their SDT status over time.

One finding is worth reiterating here: no individual improved his or her profile status over time. As such, during the early stages of one’s transition to university, no individuals improved their SDT profile membership. Moreover, with this preponderance of downward transitions, the Low profile contained members that were originally in the Low profile (19.20%), but also 69.02% ($n_{\text{Time 2}} = 127$ of 184 at Time 1) of the individuals classified as being a member of the Moderate profile at Time 1. This resulted in a Low class that was substantially larger at Time 2, than Time 1 (50.62% vs. 19.20%). Thus, Hypothesis 1.2 received support.

However, this is not to say that there were no individuals who had slightly higher SDT need satisfaction higher at Time 2, as compared to Time 1, but that there were no
individuals that experienced an increase substantial enough to experience an upwards transition in membership (Moderate to High) would be experienced. In fact, examining the scores associated with Time 1 and Time 2 SDT satisfaction would suggest that fairly large proportion of individuals (approximately 35%) demonstrated an increase in SDT need satisfaction at Time 2. However, these were generally quite trivial increases, and in absolute value terms were smaller than the average decrease experienced by the rest of the sample. Thus, although there were indeed some individuals that experienced an increase in SDT need satisfaction, after accounting for measurement unreliability, the invariance of the profiles, and fact that profile membership represents a prototypical individual and that actual participants’ scores can vary from the profile means, there were no individuals that transitioned to a higher profile.

The second insight available here is that given the negative transition, it may be of interest to consider those that maintained their initial profile membership as ideal. One would not intuitively prefer to lose their SDT need satisfaction given its close ties to well-being. There is a caveat however, in that those who maintained their Moderate or High status should be considered qualitatively distinct from those that maintained their Low profile status. Stayers in the Low profile had a zero probability of leaving that profile.\(^7\) This would suggest that a more meaningful comparison of Movers and Stayers may be gained from examining differences between those individuals that stayed in either the Moderate or High profiles and

\[^7\text{Also considered at this juncture is the evidence presented to suggest that three-profile solutions were optimal at both timepoints and were found to be structurally and dispersionally invariant. In this case, the individuals initially classified as Low members could not transition to an even lower profile because an even lower profile could not be supported (though it would be plausible to exist as the Low individuals had SDT mean scores of approximately 3.00, when the scale of measurement ranged from 1-5). Recall that the elbow plot of information criteria values occurred at the three-profile solution. Moreover, the four-profile solution was found to have very low membership size, i.e., 5.7\% of the sample, thus suggesting the four-profile solution was not optimal.}\]
those that moved from the High profile to the Moderate profile or those that transitioned from Moderate to the Low profile.

Therefore, the final step in this study’s analyses is the investigation of what differences in the well-being and resiliency variables are related to the difference between these Movers (participants that transitioned between from the High profile to the Moderate profile, and from the Moderate profile to the Low profile) and Stayers (participants that exhibited stability in their membership in the Moderate or High profiles). To explore differences across Movers and Stayers I used analysis of variance (ANOVA).

**Mover-Stayer Modeling**

In the current research, the addition of the MS latent categorical variable represented the identification of individuals who did and did not change SDT status over time. Using the MS model facilitated the examination of the resiliency attributes of those that have maintained their SDT status and those that have changed status over time. However, as I noted, because of the lack of upwards transitions, there was a qualitative difference between the Stayers of the Low profile, and the Stayers of the High and Moderate profiles. As such, rather than a standard MS, which may potentially bias the results because the Low stayers would be considered equal to those who maintained their Moderate or High status, I performed an ad hoc MS analysis.\(^8\) To do this, I only considered differences between those that stayed in the High or Moderate profiles, and those that moved downwards from the High or Moderate profiles. Therefore, based on the LTA results I developed a new variable that consisted of membership as a Mover or a Stayer, as defined by either a transition from the High profile to the Moderate profile or the Moderate profile to the Low profile (coded as 0), or stability in either the High or Moderate profiles (coded as 1). Subsequently, mean

\(^8\) Of note, as indicated by Tables 7 and 11, those classified into the Low profiles at Time 1 and Time 2 had significantly lower well-being than those in the Moderate and High profiles.
differences in the PWB and resiliency variables across the MS grouping, with a reduced sample of \( n = 323 \), were assessed using ANOVA.

As the remaining hypotheses in Study 1 considered change in the well-being and resiliency over time, these means were derived from LDS models (McArdle, 2009). Although I had previously noted that an LDS approach was not appropriate for investigating the longitudinal dynamics associated with SDT, LDS was preferable to investigate how change in the PWB and the WRI variables related to change in SDT profile membership. Thus, I used LDS models for PWB, the WRI, and the PsyCap to develop scores that accurately and reliably reflected the variable-centered change in each. Table 13 provides the model fit indices of the LDS models, and according to the CFI and RMSEA estimates demonstrated adequate fit to the data.

Table 14 presents the means of the PWB and WRI variables across the MS variable, and shows several statistically significant mean differences. In particular, the first row in Table 14 provides the mean estimates, and tests of means differences for the PWB variable. Demonstrating support for Hypothesis 1.3 is that Movers demonstrated significantly lower well-being than Stayers. Specifically, as these scores deal with LDS-based change scores, SDT profile Movers experienced significantly less well-being over time as compared to the Stayers.

Hypothesis 1.4 proposed overall mean differences between Movers and Stayers on the WRI’s resiliency variables. Table 14 shows that individuals that experienced a downward transition in their SDT need satisfaction profile membership were found to have lower PC-A, PC-B, PC-C, SRP-B, and SRP-C, and higher IR, \( F(1,321) = 7.101, 18.498, 8.236, 17.553, 7.042, \) and \( 9.002, ps < .01 \), respectively. This lends support to Hypothesis 1.4, in that Movers demonstrated less resiliency resources over time, and after experiencing adversity.
Table 13

**Latent Difference Score Model Fit Summaries**

<table>
<thead>
<tr>
<th></th>
<th>$\chi^2$</th>
<th>$\chi^2_c$</th>
<th>$\chi^2_{df}$</th>
<th>#fp</th>
<th>CFI</th>
<th>RMSEA</th>
</tr>
</thead>
<tbody>
<tr>
<td>PWB</td>
<td>42.472*</td>
<td>1.061</td>
<td>13</td>
<td>14</td>
<td>.958</td>
<td>.075 (.051 - .101)</td>
</tr>
<tr>
<td>WRI</td>
<td>1638.707*</td>
<td>1.090</td>
<td>1056</td>
<td>168</td>
<td>.945</td>
<td>.037 (.034 - .041)</td>
</tr>
<tr>
<td>PsyCap</td>
<td>426.859*</td>
<td>1.143</td>
<td>265</td>
<td>59</td>
<td>.951</td>
<td>.039 (.032 - .046)</td>
</tr>
</tbody>
</table>

*Note. n = 400. $\chi^2_c$ = scaling correction factor for $\chi^2$; df = degrees of freedom; #fp = number of parameters estimated in each model; CFI = comparative fit index; RMSEA = root mean square error of approximation, with 90% CIs in parentheses. WRI latent difference score (LDS) model estimated based on strict invariance model presented in Appendix K. PsyCap LDS model estimated latent difference of second-order PsyCap variable based on the second-order strict invariance model presented in Appendix K. Psychological Well-Being (PWB) LDS model estimated based on strict invariance model presented in Appendix K. * $p < .001.$
### Table 14

**Mover-Stayer Latent Difference Score (LDS) Means**

<table>
<thead>
<tr>
<th></th>
<th>Mover</th>
<th>Stayer</th>
<th>F(1, 321)</th>
</tr>
</thead>
<tbody>
<tr>
<td>PWB</td>
<td>-.091 (.196)†</td>
<td>.023 (.162)</td>
<td>27.023*</td>
</tr>
<tr>
<td>PC-A</td>
<td>-.068 (.359)†</td>
<td>.043 (.333)</td>
<td>7.101*</td>
</tr>
<tr>
<td>PC-B</td>
<td>-.128 (.324)†</td>
<td>.031 (.288)</td>
<td>18.498**</td>
</tr>
<tr>
<td>PC-C</td>
<td>-.071 (.278)†</td>
<td>.018 (.233)</td>
<td>8.236*</td>
</tr>
<tr>
<td>OSR</td>
<td>-.010 (.623)</td>
<td>-.017 (.546)</td>
<td>.011</td>
</tr>
<tr>
<td>IR</td>
<td>.186 (.487)†</td>
<td>-.053 (.477)</td>
<td>17.553**</td>
</tr>
<tr>
<td>SRP-A</td>
<td>-.034 (.387)</td>
<td>.020 (.343)</td>
<td>1.501</td>
</tr>
<tr>
<td>SRP-B</td>
<td>-.112 (.351)†</td>
<td>-.008 (.290)</td>
<td>7.042*</td>
</tr>
<tr>
<td>SRP-C</td>
<td>-.189 (.489)†</td>
<td>-.027 (.383)</td>
<td>9.002*</td>
</tr>
<tr>
<td>PsyCap</td>
<td>-.070 (.524)</td>
<td>.168 (.639)†</td>
<td>12.672**</td>
</tr>
</tbody>
</table>

*Note. n = 323. Standard deviations in parentheses. PC-A = Personal Characteristics – Affective; PC-B = Personal Characteristics – Behavioral; PC-C = Personal Characteristics – Cognitive; IR = Initial Response; OSR = Opportunities, Supports, and Resources; SRP-A = Self-Regulatory Processes – Affective; SRP-B = Self-Regulatory Processes – Behavioral; SRP-C = Self-Regulatory Processes – Cognitive. * p < .01, ** p < .001. † One-sample t-test against zero, p < .01.*
This suggests that those individuals who transitioned to a lower SDT profile experienced a loss in the amount of the personal protective characteristics associated with resiliency in the face of adversity. As well, Movers reported using the behavioral, and cognitive self-regulatory processes associated with resiliency and PsyCap less. The significant difference pertaining to IR suggests that SDT profile Movers rated the adversity of transitioning to university as more impactful than SDT profile Stayers over time. Notably, there were no significant differences found for the SRP-A or OSR facets of the WRI. Therefore, although not every WRI facet displayed statistically lower scores in the SDT Movers, by in large, those individuals who transitioned down in their SDT profile status had lower resiliency. These findings provide preliminary evidence to support the contention that changes in SDT need satisfaction may relate to resiliency.

**Supplementary PsyCap Analyses**

Though not the focus of the hypotheses I put forward, I also aimed to examine differences between how the PsyCap and WRI functioned in relation to SDT profile changes. Notably, as seen in Table 14, PsyCap demonstrated the opposite pattern of findings that lent support to the WRI and Hypothesis 1.4. Specifically, Stayers had higher PsyCap scores over time, whereas Movers did not experience any change in PsyCap. This might suggest that PsyCap may actually be developed through the experience of challenging life transitions.

**Discussion**

There were numerous noteworthy findings stemming from Study 1, including several that replicated those of the pilot study. The body of this Discussion will take the following outline. First, I will highlight findings regarding the longitudinal validity of the focal constructs investigated in Study 1. Second, with an eye towards demonstrating the replicability of the SDT profile solution recovered, results of the LPAs on the Time 1 and
Time 2 SDT variables will be reviewed. Finally, the association between the Time 1 and Time 2 SDT profiles will be discussed, with particular interest in exploring how change in the WRI’s resiliency variables related to the transitions between the SDT profiles at both timepoints.

**Longitudinal Validity**

Through a series of longitudinal confirmatory factor analyses the longitudinal validity and MI of the SDT, WRI, PsyCap, and PWB variables was demonstrated. The demonstration of MI is critical in any repeated measures or longitudinal study to ensure that the foundational properties of a particular measurement instrument are consistent over time (Vandenberg & Lance, 2000). Without providing evidence to support some degree of invariance (i.e., without showing at least some partial invariance), cross-time comparisons may not be valid because the actual properties of the measurement instrument may have changed (see Chan, 2011). Thus, evidence demonstrating MI lends itself to supporting the longitudinal validity of a measurement instrument (Ployhart & Vandenberg, 2010).

These demonstrations of MI across timepoints was not at the expense of accurately assessing intra-individual change, in that demonstrating MI does not exclude the possibility of change within individuals across assessment periods. Demonstrating MI, instead, means that a scale maintains its psychometric properties across timepoints, and ensures that apples are indeed being compared to apples, not oranges (F. F. Chen & West, 2008).

Using the $\Delta \chi^2$ test, and the guidelines of $\Delta$CFI < .010 and $\Delta$RMSEA < .015 (F. F. Chen, 2007; Sass, 2011) supported the invariance of the current research’s focal measures across time. In particular, all of the measures, SDT, PWB, WRI, and PsyCap, demonstrated evidence to support configural, metric, strong, strict, and factor variance/covariance invariance across Time 1 and Time 2 assessments.
That is, these MI analyses offer considerable evidence to support the notion that the SDT, PWB, WRI, and PsyCap measures function equivalently across assessment periods. This demonstration and evidence of longitudinal validity increases confidence in any cross-time comparisons made, particularly, as it might apply to estimating the difference scores between Time 1 and Time 2 assessments. Confirming that the measures used in the LDS calculations are invariant verifies that only the valid and reliable portions of the Time 1 and Time 2 assessments are used in the estimation of a difference score (McArdle, 2009). As well, ensuring the MI of the SDT variables helped in the interpretation and comparisons between the resulting LPA solutions.

**Self-Determination Theory Latent Profile Analyses**

The LPAs conducted here occupy a more central place in Study 1 than the previously discussed MI analyses. LPA was used to identify separate classes or profiles of individuals based on the satisfaction of their basic psychological needs, as defined by SDT. Similar to my previously published examples of research using LPA (McLarnon et al., 2015; O’Neill et al., in press), this method allowed me to examine the heterogeneity contained within a single sample of data, as presented by distinct subpopulations. Here, the subpopulations were discrete classes of individuals defined by different levels of SDT need satisfaction.

LPA, although overcoming many of the shortcomings of traditional person-centered analytical approaches like cluster analysis, are not beyond reproach. For instance, even though LPA offers a more objective perspective on the number of profiles underlying a set of data as compared to cluster analysis, there is still the need to involve researcher judgment in determining optimal profile enumeration. To this end, for both of the LPAs investigated here for Time 1 and Time 2, I offered a comprehensive set of model-fit statistics (see Tables 4 and 8). In particular, referring back to the results noted above, I based my decision to retain a
three-profile solution from the Time 1 and Time 2 SDT LPAs because the three-profile solutions offered a significant improvement (i.e., BLRT p-value < .05, substantially lower AIC, CAIC, BIC, and aBIC values) over the two-profile solution. Moreover, the four-profile solution was found to only offer a trivial improvement in model fit (see Figures 2 and 4), suggesting that the extra profile of individuals was spurious in nature. Therefore, in the interest of endorsing the best-fitting, yet most parsimonious model, I retained the three-profile solution as optimal for the Time 1 and Time 2 data.

Comparing the Time 1 and Time 2 three-profile solutions (see Figures 3 and 5) suggested a high degree of similarity of solutions across timepoints. This similarity increased my confidence in the adequacy of these Time 1 and Time 2 three-profile solutions, and further supported my contention that the three-profile SDT LPA solution was optimal. These profiles, as depicted in Figures 3 and 5, were labeled as Low, Moderate, and High, based, relatively speaking, on how highly participants rated their autonomy, competence, and relatedness basic psychological need satisfaction.

In fact, the high degree of similarity across the pilot test, Time 1, and Time 2 solutions offer a very strong degree of certainty that the three-profile solution is optimal. Thus, another noteworthy finding stemming from Study 1 is the similarity of SDT profiles recovered from the pilot test, and the LPAs conducted on the Time 1 and Time 2 assessments, despite totally independent samples and the use of different SDT measures.

Even though both the pilot test and Study 1 were conducted in the same context, and tapped the same general population of undergraduate students, the cross-validation of profile results is valuable. Although one could argue that the similarity between the Time 1 and Time 2 profile solutions could have resulted from sample-specific attributes, the comparison to a totally separate sample in the pilot test should minimize this concern. Likewise,
recovering the same profile solution in Study 1 as compared to the pilot test becomes even more noteworthy because of using a different SDT measure. Thus, the recovery of three SDT profiles, Low, Moderate, and High, also does not appear to be due to the specific characteristics of the SDT measure used. Thus, the three-profile solution appears to be robust to sample- and SDT measure-specific characteristics.

The relations observed between the profiles and the psychological well-being variable also substantiated the three-profile solution. Well-being measures were collected in each assessment as a means to provide evidence of construct validity of the profile solutions. This was because SDT need satisfaction should be positively related to well-being. Therefore, to provide evidence of construct validity of the profile solutions, which should have differential levels of well-being, well-being was treated as an outcome of the SDT profiles. The aim was to validate the notion that the individuals classified as being a member of the High profile did indeed have higher well-being than those individuals classified into either the Moderate or Low profiles. At both timepoints the High profile was found to have significantly higher well-being than the Moderate and Low profile groups. As well, the Moderate profile was found to have significantly higher well-being than the Low profile. Thereby, providing evidence of construct validity for the three-profile solutions.

Recovering such highly similar profiles across the pilot test, and the Time 1 and Time 2 assessments is also notable in comparison to the literature applying LPA to the study of organizational commitment. In fact, comparing the results of Kam et al. (in press), Meyer et al. (2012), Meyer, Kam, Goldenberg, and Bremner (2013), and Morin, Meyer, McInerney, Marsh, & Ganotice (2015) would suggest only a moderate degree of consistency in optimal profile solutions. Despite using the same organizational commitment measure (i.e., Meyer, Allen, & Smith, 1993) these four studies have differential concluded that five or six profiles
are optimal. Kam et al. and Morin et al. supported a five-profile solution as optimal, whereas Meyer et al.’s two studies supported six-profile solutions. In this case, the profile solutions of Kam et al. and Meyer et al. would not demonstrate configural invariance (see Morin et al., 2016). In contrast, the current research presented highly consistent three-profile solutions across the Time 1 and Time 2 timepoints.

The three-profile solutions I determined to be optimal from the pilot study and Study 1 are somewhat similar to the findings of Ratelle et al. (2007). Although there are several important differences between Ratelle et al.’s study and those that I have conducted, across three independent samples Ratelle et al. determined that three profiles was optimal. Despite this consistency, Ratelle et al. actually approached the study of SDT profiles from a motivation perspective. As input for their profile analysis five indicator variables tapping intrinsic motivation, identified regulation, introjected regulation, external regulation, and amotivation were used. In this way, Ratelle et al. refer the focus of their analysis as the derivation of “profiles based on SDT types of motivation” (p. 736). Thus, despite dissimilarity between the focal indicators used in the profile analyses, Ratelle et al. used variables that were conceptually similar to the SDT variables I have used, that play a more proximal role in well-being rather than motivation. But again, despite these differences, the general results from Ratelle et al. and the analyses I have conducted were remarkably similar, and thus, further support the veracity of Study 1’s findings.

A final point of similarity emerges here between the profile solutions offered by the pilot test and those from Time 1 and Time 2 of Study 1, and the results of Ratelle et al. (2007). Ratelle et al.’s optimal profile solutions were also predominantly differentiated on the basis of level. In fact, Ratelle et al. also invoked Low, Moderate, and High labels to describe the profiles recovered. Thus, it appears that the three-profile solution with predominantly
level-only differences of the SDT variables is quite robust. In fact the LPA solutions I have shown here have demonstrated a strong degree of replicability and generalizability, and thus provide validity to this study’s results.

Although I noted in the previous section that the three-profile solutions recovered from the Time 1 and Time 2 SDT assessments displayed a high degree of similarity, I also conducted tests of equivalence between the profile solutions. Here, the Time 1 and Time 2 profile solutions demonstrated configural, structural, and dispersional invariance. In contrast to the MI tests noted above from the LCFA models, these invariance tests focus on the profile groups recovered from the LPAs, not the functioning of the SDT survey instruments. As an additional test of profile invariance I had also assessed distributional invariance, which built upon the invariance stages of configural, structural, and dispersional to include additional equality constraints on the proportion of the sample allocated to each profile. However, according to all of the fit indices considered (LRT, and the AIC, CAIC, BIC, and aBIC information criteria), there was little evidence available to support distributional invariance of the Time 1 and Time 2 profile solutions. Lack of distributional invariance suggests significantly different proportions of the sample were occupying each profile at each timepoint. Therefore, there was significant mobility in individuals’ SDT need satisfaction profile membership over time. This mobility, and distributional non-invariance took the form of a general downward trend in membership.

This does not mean, however, that every individual experienced a decline in his or her SDT need satisfaction. Indeed, some individuals did experience an increase in SDT need satisfaction scores, but these increases were only trivial and not substantial enough to suggest an upward transition in profile membership. Up to this point, I have demonstrated considerable evidence of stability and consistency of measurement, but the next stage of my
analyses were to provide a perspective on who maintained their SDT need satisfaction status, and who transitioned to a different, lower, SDT profile over time. I was justified in continuing this line of inquiry, despite the lack of distributional invariance because Morin et al. (2016) suggested that further analyses on the combined modeling of LPAs could be conducted when at least configural and structural invariance has been supported. Thus, the next step of my analyses was to examine what types of transitions were present and, critically, how the WRI and PsyCap variables could be used to characterize those that have transitioned and those that have maintained their status.

**Self-Determination Theory Profile Transitions**

The proportions presented in Table 12 suggested a substantial degree of variance in terms of the number of cases that maintain their status and those that do transition. In fact, 53.86% of cases (n = 215) transitioned between Time 1 and Time 2 profiles. On the other hand, 46.13% of cases (n = 185) maintained their SDT profile status. Two points are notable about these proportions.

First, all of the individuals that transitioned into a different profile experienced a downward transition in membership. In other words, all of the transitions exhibited were of a downward nature, and there was no evidence to support any individuals experienced transitions into better profiles. I had suggested this above based on the lack of distributional invariance from the previous stage of LPA-based MI analyses, but here, the observed are obvious – all of the transitions between Time 1 and Time 2 SDT need satisfaction profiles were negative. Thus, the transition to university was predominantly found to be a negative experience, as none of the individuals reported a positive transition over time. Or in unequivocal terms, no individual was a member of a more positive need satisfaction profile at Time 2 than they were initially classified in at Time 1.
The finding that there were no positive transitions sets the stage for the second notable point about these transitions. In particular, if an individual was a member of the Low profile at Time 1 there was a 100% probability that he or she would be a member of the Low profile again at Time 2. Again, however, this does not preclude the possibility that some Low members’ scores may have slightly increased over time, these score increases were not substantial enough to demonstrate a transition into the Moderate profile. Though unfortunate, this underscores the challenging nature of a significant life transition, such as the transition to university.

In general terms for a Mover-Stayer LTA model this would mean that those cases initially assigned to the Low profile would be considered Stayers. However, given the valence associated with membership, in that the Moderate and High profiles were validated as having higher PWB, I proposed that being a *stayer* in the Low class was sub-optimal. Thus, given that the next component of Study 1 was to examine who maintained their status and who changed status I excluded those that were initially classified as a Low member. This was because the current study did not reveal any individuals that experienced an upward transition in profile membership. In particular, these findings revealed no evidence to support the upward transition from the Low profile to the Moderate profile, nor the Moderate profile to the High profile, nor the Low profile to the High profile for any individual over the two assessments involved in the current study. Had I considered those with a Time 1 Low status as Stayers, the resulting comparison with the resiliency variables would have been biased. Thus, they were excluded from the MS analyses to obtain a clearer picture of how the resiliency variables characterize those that moved from the Moderate to Low profiles or High to Moderate profiles and those that stayed in either the Moderate or High profiles.
Before moving on, however, it may be interesting to consider this specific subgroup of individuals. In particular, although upwards transitions may have been theoretically possible, and could have emerged in the analyses conducted, individuals initially classified into Low could not transition out of the Low profile. Based on the review of Z. E. Taylor et al. (2014), which led to the development of Hypothesis 1.2, the transition to university is a challenging and adverse experience for most individuals. As such, there would only be individuals that maintained their initial SDT status and those that transitioned to a lower SDT need satisfaction group. Given the adversity associated with transitioning to a university environment, it would be very difficult for individuals to transition to a better need satisfaction profile group. Results supported this proposition. However, the results also suggested that although that individuals classified into the Low group did not improve their standing, they also did not get any worse. This would suggest something of a “basement effect” (see also Footnote 7). Despite being exposed to the same challenges as individuals in the Moderate or High classes, Low individuals’ SDT need satisfaction or well-being wasn’t additionally impacted during the transition to university. This might suggest that those initially classified as Low are just getting by, so to speak, and may have already reached the subjectively lowest point in their well-being.

The finding that there were no positive transitions in membership over time presents an interesting, yet concerning result. As noted, this meant that one’s initial profile determined which profile an individual could transition into by the follow-up assessment. In particular, if an individual was in the Moderate profile at Time 1, by the Time 2 assessment there was only the probability that the individual was a member of the Moderate profile or Low profile, not the High profile. Given one’s initial profile as Moderate or Low, there was a zero chance of
becoming a member of the High or Moderate profiles, respectively, at Time 2. Moreover, with a greater portion of individuals experiencing downward transitions there was a higher probability of experiencing a downward trajectory, rather than maintaining one’s initial membership. This in fact, speaks to the adversity experienced by students transitioning to a university environment.

**Mover-Stayer Modeling of SDT Profile Transitions and Association with Well-Being**

Whereas Hypothesis 1.1 focused on the cross-sectional relations between SDT profile membership and PWB, which was supported, Hypothesis 1.3 focused on the relation between change in SDT profile status and change in well-being. Hypothesis 1.3, therefore, was positioned to provide evidence of construct validity of the MS variable. As shown in Table 14, Movers and Stayers demonstrated a significant difference in changes in PWB levels, and a strong effect size, $d = .615$, 95% CI = .377 - .853 (Cohen, 1988). Thus, whether an individual was classified as either a SDT profile Mover or an SDT profile Stayer was strongly associated with his or her well-being, providing evidence of construct validity of the MS variable. Moreover, if one transitioned down from the High group to the Moderate profile group or transitioned down from Moderate to Low, well-being was substantially less than for an individual that maintained either his or her Moderate or High SDT need satisfaction profile membership.

**Mover-Stayer Modeling of SDT Profile Transitions and Association with Resiliency**

Because there were no positive transitions, the subsequent analyses that explored the differences between SDT profile movers and stayers was really about which variables helped maintain well-being, rather than which provided a boost to well-being. This corresponds to

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9 Again, this does not preclude the possibility of an individual experiencing a minor increase in SDT need satisfaction scores, but that the increases are not substantial enough to transition the individual into the Moderate profile from the Low Profile, or the High profile from the Moderate profile.
Masten’s (2001; see also Garmezy, 1981, 1991; Werner & Smith, 1982, 1992) emphasis on protective factors, in that central features of resiliency are about traits and processes that guard one’s well-being against the experience of negative or challenging events.

Having said that, it is worth reiterating the point that Study 1’s main objective was an exploration of how changes in SDT need satisfaction relate to changes in resiliency. Here, Study 1 offered an estimate of the relations between changes in SDT need satisfaction during a challenging life transition and changes in WRI and PsyCap variables. One consideration to keep in mind is that given the shorter, and naturalistic pre-/post-, research design, Study 1 examined which resiliency variables changed during the early stages of a challenging experience. Furthermore Study 1 assessed the relation between changes in SDT need satisfaction and changes in resiliency.

With a focus on change experienced within the WRI and PsyCap variables during the transition to university, difference scores were computed using McArdle’s (2009) LDS approach. Notably, the derivation of the LDS scores was easily facilitated by the CFA-based MI analyses (see Appendix K). These LDS models represented reliable and valid components of the differences between each respective Time 1 and Time 2 of the PsyCap and the eight WRI facets (see McArdle, 2009). Table 13 presented the mean LDS scores of each of these variables, across those individuals that experienced a downward SDT transition and those that maintained their SDT status.

Moreover, Table 14 also presents the results of ANOVAs comparing mean LDS scores across SDT profile Movers and SDT Stayers, t-tests against zero within each Movers and Stayers. From a general perspective, Movers demonstrated greater change in the WRI and PsyCap variables over time. In particular, Movers’ deviation from zero in the LDS-derived scores occurred in more variables than Stayers’ LDS scores. Movers’ PC-A, PC-B,
PC-C, SRP-B, and SRP-C LDS were all in the negative direction. It is also plausible to consider increased IR as negative, as that would suggest that the transition experience has been perceived as more negative over time. Thus at the Time 2 assessment, Movers had significantly less PC-A, PC-B, PC-C, SRP-B, and SRP-C and higher IR. On the other hand, Movers had significantly greater IR at the follow-up. No significant change over time was found for either the OSR or SRP-A components of the WRI. On the other hand, Stayers did not show significant change in any of the WRI components over time.

Thus, change in SDT profile membership over time, in response to a challenging life transition, accompanied a significant decrease in several of the WRI’s components, and an increase in how adversely the life transition was perceived. Moreover, at the follow-up assessment, Stayers were generally found to have higher levels of resiliency than Movers. This suggests a relation between resiliency and SDT need satisfaction, in that those who have experienced a substantial change in need satisfaction will also experience a change in resiliency, but those who have not experienced a change in SDT need satisfaction will not experience any difference in resiliency. The opposite pattern of findings was found for the PsyCap variable. Stayers demonstrated more change in the PsyCap variable during the transition to university. In this case, Movers had no significant change in PsyCap, but Stayers experienced an increase over time. In light of fundamentals of COR theory, experiencing a downward SDT profile transition is associated with losing one’s resiliency resources, suggesting that the resources are being expended in effort to restore well-being. Future research, will be necessary to explore if Movers are able to restore their well-being, and over what duration this restoration occurs.

Together, Movers experienced a greater change in six of the eight WRI components (PC-A, PC-B, PC-C, SRP-B, and SRP-C, and IR), and the Stayers experienced greater
change in the PsyCap variable during the transition to university. The results regarding the PC variables are interesting given Masten’s (2001) perspective on resiliency being a function of various protective factors. In particular, maintaining the capacities an individual has available to sustain a sense of emotional well-being (PC-A), preserve a sense of self-efficacy (PC-B), use mean-making techniques (PC-C), and use cognitive and behavioral self-regulation (SRP-C and SRP-B, respectively) over time is related to maintaining well-being in the face of challenging situations. Those that had moved SDT membership downward had significantly lower PC-A, PC-B, and PC-C, suggesting, within the bounds of correlational and non-experimental research, that those who have less of these resiliency characteristics at follow-up have experienced substantial adversity. Thus, those that experienced a decrease in SDT standing are likely to have lower levels of the affective, behavioral, and cognitive protective factors associated with resiliency. Thereby suggesting that resiliency may only be necessary when SDT has been substantially negatively impacted.

Change in SDT need satisfaction profile membership, therefore, offers a potential explanation for what circumstances necessitate resiliency. Consider the SDT profile movers. As a group, they have all experienced a decrease in their combined autonomy, competence, and relatedness need satisfaction. This decrease in SDT need satisfaction profile status was accompanied by a decrease in PWB, whereas the SDT profile Stayers did not experience any change in PWB (see Table 14). This decrease in SDT and well-being, went hand-in-hand with a decrease in several of the resiliency attributes (i.e., PC-A, PC-B, PC-C, SRP-B, and SRP-C). On the other hand, the individuals classified as Stayers maintained their autonomy, competence, and relatedness need satisfaction, and therefore their well-being. Stayer status was also associated with a lack of change in the resiliency variables over time. In particular, they did not report using any of the protective factors or self-regulatory processes any
differently (in terms of more or less) at the follow-up assessment as compared to the initial assessment. This becomes even more enlightening when there are only significant differences in OSR and SRP-C between Movers and Stayers at Time 1. As depicted in Appendix N, Stayers have higher OSR and SRP-C (and PsyCap). On the other hand, Movers and Stayers did not differ significantly on the PC-A, PC-B, PC-C, IR, SRP-A, and SRP-B components of resiliency. Before the experience of adversity, those that eventually transitioned downward generally had the same level of resiliency resources, except for lower social support and cognitive self-regulation. Thus, individuals experiencing a challenging event or life transition, and the accompanying loss of SDT need satisfaction will need the effective use of resiliency-related protective factors and self-regulatory processes in order to maintain well-being.

Interestingly, the same effect was also found for the WRI’s IR facet, albeit the direction of the mean difference is switched from the previous discussion (see Table 14). Movers reported a significant increase in IR, which was also significantly greater than the change reported by Stayers over time. Here, Movers considered the transition to university as more adverse than Stayers over time. Thus, at the follow-up assessment, individuals classified as a SDT profile Mover got worse (i.e., PWB was lower) during the transition to university, rated the transition as more severe, more stressful, and as causing more disequilibrium (i.e., IR was higher), than those classified as Stayers. This helps link the notion that challenging life events that decrease SDT need satisfaction require resiliency because they are rated as more severe and adverse over time.

Individuals that experienced a negative change in SDT status over time similarly experienced a reduction in resiliency, as compared to those that have maintained their SDT status. Thus, Masten’s (2001) personal resources perspective appears to be only part of the story. The reduction in PC-A, PC-B, PC-C, SRP-B, and SRP-C is consistent with the
propositions of COR theory (Hobfoll, 2002; Wright & Hobfoll, 2004). Recall that resiliency was earlier proposed to be an active and effortful process and phenomenon. According to COR, demonstrating resiliency would in effect be associated with expending one’s resources, and given a finite amount of resources (as no resiliency-related intervention was given), those individuals exercising their resiliency would demonstrate lower levels upon follow-up. By linking change in SDT need satisfaction with negative changes in resiliency, Study 1 suggests that events or experiences that have reduced one’s SDT need satisfaction, will require resiliency to achieve, or restore, previous well-being. Thus, resiliency may only be necessary when there are substantial drops in one’s SDT need satisfaction.

This stems from the evidence presented above that suggests that if one’s SDT status is not impacted then there will be no change in resiliency. Having demonstrated that Time 2 scores were lower than Time 1 scores (for the PC-A, PC-B, PC-C, SRP-B, and SRP-C facets of the WRI; higher Time 2 scores than Time 1 for the IR facet) for Movers helps support COR theory. According to COR theory, this is because the reduction in the protective factors and self-regulatory resources associated with resiliency, suggests that the resources have been used. On the other hand, maintaining one’s SDT status was associated with maintaining one’s resiliency resources. This stems from the lack of significant changes of the WRI facets in the SDT profile Stayers. Although these results are indeed consistent with the propositions of COR theory, a carefully controlled experimental study will be necessary to support that there has been an active attempt by the individual to restore well-being by expending their own resources.

The experience of challenging events, here considered to be the transition to university an environment, diminished the SDT need satisfaction of some individuals. These individuals experienced a greater drop in resiliency than those that did not experience a
change in SDT need satisfaction. Thus, there was a negative relation between SDT need satisfaction and resiliency during the experience of a challenging event. On the other hand, within individuals that did not experienced a decrease in SDT need satisfaction there was no evidence of change in resiliency change over time. Therefore, those individuals that did not experience any decrease in his or her SDT need satisfaction did not experience any change in the activity of his or her resiliency protective factors or self-regulatory process.

Events that substantially reduce SDT will accompany a reduction in resiliency as an individual attempts to restore well-being. Thus, the nature of a challenging event that will necessitate resiliency is that it substantially reduces one’s SDT need satisfaction, and qualitatively reduces how highly one’s SDT needs are satisfied. Resiliency, therefore, is associated with SDT need satisfaction changes substantially.

One additional consideration is the relation between change in resiliency and change in the psychological well-being outcome. I have refrained from examining these relations in Study 1 as the focus has been on examining the relation between changes in SDT and changes in resiliency. Study 2, on the other hand, is focused on the relations between changes in resiliency and changes in two important outcome variables. Interested readers are referred to Appendix O, which provides a correlation matrix that demonstrates generally significant and positive relations (negative in the case of IR) between changes in resiliency and changes in PWB. One reason that I have refrained for interpreting these relations in depth is that Study 1 involved a pre-/post- design and that well-being was only assessed before and after the experience of an adverse event, rather than longitudinally after a challenging event. Study 2, therefore is in a stronger position to examine relations between resiliency and well-being as they unfold over time, rather than a snapshot of change before and after an adverse event.
Psycap Resources

As noted, the relation between changes in Psycap and changes in SDT need satisfaction profile membership differed in direction from the relations observed for the WRI’s facets. The WRI facets demonstrated decreasing levels in association with SDT reduction. Whereas in individuals that maintained their SDT status, no change in the WRI was demonstrated. On the other hand, when SDT reduction is experienced, Psycap maintains a relatively static level, but if SDT status is maintained Psycap may grow. Psycap then, appears to be a resource that is not associated with the adversities experienced during a challenging life transition. At a basic level, this would provide further evidence of discriminant validity (see McLarnon & Rothstein, 2013), in that the WRI and Psycap tap fundamentally different constructs within the domain of positive psychology. The WRI taps resiliency-based resources that function in relation to a substantial reduction in SDT need satisfaction, whereas the Psycap resources may build during periods in which SDT need satisfaction is maintained.

The main takeaway message from Study 1 is that experiences that reduce the satisfaction of one’s SDT needs are associated with lower resiliency resources over time. Whereas maintaining one’s SDT profile status is related to maintaining consistent levels of one’s resiliency resources over time. Stemming from this, several implications may be offered. In addition, to conclude the Discussion of Study 1 I offer several limitations that readers may wish to consider in conjunction with the evidence I have presented here.

Implications

The SDT need satisfaction-based transitions explored by Study 1, and their relation with resiliency-related variables are likely to be of interest to several audiences. The transitions documented here may be of interest to university administrators that have to
contend with the influx of new students every year. Particularly in light of several recent popular media stories on the adversity experienced by new undergraduate students (e.g., Kennedy, 2013), the results documented here would support universities’ initiatives meant to supplement students’ transition to university. Particularly, the results offered here would support the generation and development of new programs and policies focused on bolstering resiliency resources, and improving autonomy, competence, and relatedness need satisfaction during the early stages of one’s undergraduate education. Additionally, the results offered by Study 1 would support the development and implementation of programs meant to equip students with the skills, abilities, and knowledge to better deal with the difficulties one is likely to encounter in the early stages of one’s university education. In particular, Doll, Eslami, and Walters (2013) noted that many instances of dropping out from school are due to various reasons like receiving poor grades, not getting along with teachers or other students, or not enjoying the school environment. If resiliency resources and autonomy, competence, and relatedness need satisfaction are bolstered then one may be more easily able to cope with the challenges of an educational environment, and may be better able to tolerate situations in which one’s sense of competence, relatedness, and autonomy are challenged. Of note, the University of Western Ontario has recently initiated the 1010 program, a series of online modules aimed at helping students navigate the transition to university successfully.

In the same vein, the results presented here may also be of interest to organizations faced with substantial onboarding challenges (T. N. Bauer & Erdogan, 2011). As a component of new employees’ training, socialization, or realistic job preview, providing opportunities to exercise and further develop one’s SDT, WRI, and PsyCap resources would likely enable improved tolerance of the challenging transition involved with joining a new
organization. Thus, the results of Study 1 also support organizations initiating programs focused on improving the well-being of its employees.

The finding that PsyCap increased, but none of the WRI facets did for the SDT Stayers, suggests that PsyCap may be built implicitly when one’s SDT profile status is maintained. Thus, although Luthans et al. (2006), Luthans, Avey, and Patera (2008), and Russo and Stoykova (2015) have documented the effectiveness of increasing PsyCap levels through a specially-designed training program, it appears that PsyCap can increase, on its own, when one’s SDT status is preserved. On the other hand, S. J. Peterson et al. (2011) documented a longitudinal decline in PsyCap in a sample of financial advisors, who, following the 2008 economic meltdown were likely under considerable pressure and stress. S. J. Peterson et al. argued that the observed decline in PsyCap in that sample, without the exposure to a PsyCap intervention was intuitive. On the other hand, increasing the WRI-based resources will likely take a targeted development program or intervention to explicitly encourage growth and development of the resiliency components tapped by the WRI.

**Limitations and Directions for Future Research**

Although the presentation of evidence to support MI was an important stepping-stone in the assessment of longitudinal validity, the accumulation of evidence to support a measure’s validity is never-ending (Schwab, 1980). As such, future research should be conducted to investigate the MI of Study 1’s focal measures across longer assessment periods, and across additional measurements. Investigating the MI properties of these measures across longer time lags, and across three or more assessment periods will allow for a more comprehensive understanding of the longitudinal validity of these measures. Study 2 will in part address this, but it may still be of interest to examine the longitudinal validity of these measures over longer durations.
Although not hypothesized due to the nature of adversity that the current sample was likely undergoing, the lack of upwards transitions is also somewhat of a limitation. In other contexts and samples it would have been possible for LTA to uncover some individuals that flourished during a challenging life transition. This would have been exhibited, for example, by individuals transitioning from the Moderate SDT profile at Time 1 to the High SDT profile at Time 2. Positive, or upward, changes in SDT need satisfaction membership might have been related to increasing usage of the protective factors and self-regulatory processes, thus providing evidence of a positive relation between SDT need satisfaction over time and resiliency. However, since positive transitions across the SDT profiles were non-existent, it was not possible to draw any conclusions regarding these transitions. The resounding contribution offered, instead, is that decreasing SDT need satisfaction is related to decreasing resiliency, and that in order to maintain one’s SDT profile status, more, or at least roughly the same level of resiliency will need to be exercised while navigating the challenging event. Although this is not likely to be the full cause for the need for resiliency, the importance of Study 1’s findings should not be diminished. If an event has been experienced, that does not reduce the satisfaction of one’s SDT needs then it is unlikely that resiliency is necessary because the event has not had a significant enough impact.

As this study was longitudinal in nature, the effects of participant drop-out may be a limitation. Following the guidelines of Goodman and Blum (1996) I assessed the potential effects of non-random drop-out on this study’s variables. As demonstrated through a logistic regression and an independent samples t-test, PCC was found to be higher in individuals who did not respond to the Time 2 survey. However, this difference was not reflected in differences in variance, nor was found to moderate any of the relations between the other variables involved with this study. Thus, despite the finding that PCC differentially predicted
attrition at Time 2, these effects were negligible, and did not result in any differences in variances or differential relations between the focal variables, therefore minimizing these potential concerns and limitations.

Generalizability of the results to other populations is also not beyond reproach. I have aimed to study one specific population, students, undergoing the transition to university. Future research and replication will be necessary to generalize these findings to other populations. However, arguments forwarded by Ilgen (1986) and Locke (1986; see also Highhouse & Gillespie, 2009) have suggested that these types of convenience samples aren’t as detrimental as commonly thought, and help support their use here. In Study 2 I offer a complementary examination of resiliency and change over time, but without the explicit focus on SDT because Study 2 was conducted with employees who had been laid off and were undergoing an outplacement transition. In this way, a pre-transition measurement was not available, and thus would not have rendered an understanding of individuals’ SDT need satisfaction over time in response to the transition.

**Conclusion**

Study 1 offered an exploration of the conditions and changes necessary that impact changes in resiliency. Following a rigorous examination of the measurement invariance of the constructs and variables assessed over time, profiles of individuals’ SDT need satisfaction were developed. As a three-profile solution, characterized by increasing levels of need satisfaction, was found to be optimal across an independent pilot study, and demonstrated invariance across repeated measures. Despite the evidence supporting invariance, it was also found that a substantial proportion of individuals (53.86% of the sample) transitioned to a worse profile over time. Interestingly there were no upwards transitions, and thus the remainder of the sample (46.14%) retained their initial profile status.
Subsequently, individuals that changed profiles (Movers) were compared to those that maintained their profile (Stayers) in regards to psychological well-being and variables tapped by the WRI and the PsyCap. Psychological well-being was lower in those individuals who experienced a downward transition, thus providing evidence for the validity of the profile transitions. Moreover, Stayers demonstrated a relatively constant level of the resiliency components tapped by the WRI, but experienced an increase in those tapped by the PsyCap. On the other hand, Movers experienced a decrease in resources tapped by the WRI, but static levels of PsyCap. This suggests, in brief, resiliency may only become active when SDT status changes significantly, but that the resources tapped by the WRI and PsyCap are fundamentally different, yet play a complementary role in differentiating those individuals that have conserved their need satisfaction versus those who have experienced a decrease in need satisfaction.
Study 2

The second study of this dissertation focuses on the actual nature of the trajectory of resiliency over time and aims to provide a contextualized picture of the relations between change in resiliency over time and change experienced in well-being and a contextually-relevant outcome variable. These broad aims comprised the focus of Study 2: to build the body of knowledge surrounding the King and Rothstein (2010) model and the WRI measure, a longitudinal investigation into the role of resiliency, as it unfolds in response to a specific, challenging event was necessary. The stage for this broad research aim was set by the study of S. J. Peterson et al. (2011), who examined the PsyCap model over time, and the effect of change in PsyCap on subsequent job performance.

Recall that a considerable amount of evidence has amassed to support the malleable nature of PsyCap over time (e.g., S. J. Peterson et al., 2011; Luthans, Avey et al., 2010; Luthans, Avey et al., 2008), which has supported the state-like propositions of the PsyCap model (e.g., Luthans, Youssef et al., 2007). However, also recall that the PsyCap model and measure may present an insufficient perspective on resiliency. Thus, before more definitive conclusions are drawn on the role among the components of resiliency and important outcome variables, it is argued that resiliency, as hypothesized by King and Rothstein, be investigated over time, and in relation to important outcome variables.

Resiliency after the Experience of Job Loss, and During the Search for New Employment

Much previous research has discussed the profound implications of job loss for one’s well-being. Losing one’s job has been linked to lower life quality, life satisfaction, and self-esteem (Caplan, Vinokur, Price, & van Ryn, 1989; Grün, Hauser, & Rhein, 2010; Wanberg, 1995), and increased perceived stress and depressive symptoms (Leanal & Feldman, 1990;
RESILIENCY AND WELL-BEING

Kinicki & Latack, 1990). Furthermore, meta-analyses and other comprehensive literature reviews have evidenced the substantial negative impact on mental health and well-being following job loss (McKee-Ryan, Song, Wanberg, & Kinicki, 2005; Paul & Moser, 2009; Wanberg, 2012). Thus, as one’s job is closely linked to one’s identity (Kinicki, Prussia, & McKee-Ryan, 2000; Latak, Kinicki, & Prussia, 2002; Price, Friedland, & Vinokur, 1998; Price, Choi, & Vinokur, 2002; Price, & Fang, 2002), it should not be surprising that the experience of losing one’s job will have profound negative effects on an individual’s well-being.

After losing one’s job, the logical next step is to undertake the search for new employment. However, the path to securing a new job is often wrought with difficulty, challenges, and disappointment (Côté, Saks, & Zikic, 2006; Fleig-Palmer et al., 2009; Saks, Zikic, & Koen, 2015). The importance of self-regulation in succeeding in one’s job search has recently been highlighted and discussed by several studies (e.g., Liu, Huang, & Wang, 2014; Turban, Lee, da Motta Veiga, Haggard, & Wu, 2013). This conceptual alignment between the King and Rothstein (2010) model of resiliency (including the role of self-regulation), and the experience of losing one’s job, suggests that the WRI may be optimal for use in research investigating the experience of job loss, and may be advantageous as compared to the PsyCap. Turban et al. (2013) found that self-regulation, in the form of motivation and procrastination control, was significantly related to successfully navigating the job search process. Turban et al. reasoned that during the job search effective self-regulation would be required by individuals to manage one’s thoughts and behaviours to maintain a productive job search (see also Kanfer, Wanberg, & Kantrowitz, 2001; Wanberg, Kanfer, & Rotundo, 1999). Additionally, studies completed by Wanberg, Zhu, and Van Hooft (2010) and Wanberg, Zhu, Kanfer, and Zhang (2012) suggested that since the job
search is an arduous and stressful process, controlling one’s negative emotions will help job seekers conduct a more effective job search (see also McCarthy & Goffin, 2004). Thus, a conceptual linkage is forged between the process of rebuilding following job loss and several of the aspects associated with the King and Rothstein (2010) model and the WRI.

As resiliency may offer the means by which an individual will return to normal functioning and performance following an adverse event, Study 2 aimed to investigate the role of resiliency in rebuilding and restoring an individual’s well-being following dismissal from a previous job. It is critically important to investigate the King and Rothstein (2010) model and the WRI over time, to examine the dynamic nature of resiliency as it functions in response to an adverse event. Thus, Study 2 aimed to provide a longitudinal analysis of the WRI facets over time, and second, to examine the relation between change in the WRI facets over time and an individual’s well-being following the experience of job loss.

Whereas S. J. Peterson et al. (2011) were able to benefit from a fairly large body of research on the state-like nature of PsyCap in proposing their longitudinal hypotheses, the same is not possible for the WRI and King and Rothstein (2010) model. In particular, although King and Rothstein (2010) suggested that resiliency is a process-based construct, and should exhibit a dynamic nature as it unfolds over time, the previous research using the WRI has been cross-sectional and isn’t in a position to inform explicit hypotheses over the nature and trajectory of change over time. On the other hand, S. J. Peterson et al. were able to rely upon the earlier study of Norman, Avolio, and Luthans (2010), which found support for linear changes in PsyCap in response to feedback from one’s leader. As evidence supporting a linear, or non-linear, trajectory was not available prior to this study, I refrained from stating an explicit hypothesis, and rather investigated the nature of the trajectory of resiliency in accordance with a research question:
**Research Question 2.1.** What is nature of the trajectory (i.e., linear or non-linear) of resiliency over time in response to losing one’s job?

As noted, the second broad aim of Study 2 was to investigate the relations between change in resiliency and change in well-being and a contextually-relevant outcome variable important for one’s search for new employment, job search self-efficacy. As reviewed above, job loss has profound negative effects for one’s well-being. In particular, McKee-Ryan et al. (2005), Paul and Moser (2009), and Wanberg (2012) noted that following job loss well-being was substantially reduced. Therefore,

**Hypothesis 2.1.** After a job loss, change in the resiliency components will account for a significant proportion of variance in change in psychological well-being over time.

Recently, Liu, Huang, and Wang (2014) have recently discussed the role job search self-efficacy (JSSE) may play as a predictor of employment status. In their view, JSSE occupied a central role in the search for new employment, in that JSSE motivated actual job search behaviors, which then led to achieving new employment. As well, Liu, Wang, Liao, and Shi (2014) found that JSSE contributed to job applicants’ actual job search behaviors (i.e., networking and sending in resumes) and the number of job offers obtained during the search for employment. Of note, Liu, Wang et al. found that JSSE contributed positively, whereas a generalized form of self-efficacy contributed negatively. This speaks to the need to use a contextually-appropriate form of self-efficacy, as generalized self-efficacy may not be theoretically appropriate for all contexts and outcome variables. As well, Saks et al. (2015) have recently regarded the JSSE construct as one of the most studied by job search research, and suggested that it represents a construct integral in determining the success of one’s job search. Therefore,
**Hypothesis 2.2.** After a job loss, change in the resiliency components will account for a significant proportion of variance in change in job search self-efficacy over time.

Throughout Hypotheses 2.1 and 2.2, the relations between changes in PsyCap and changes in the two outcomes examined will also be examined through hierarchical multiple regression models. These hierarchical regression models will allow me to explore whether the PsyCap helps explain additional variance in both outcome variables above and beyond the variance explained by the WRI facets.

As noted above, I have positioned the current research to fulfill several of Ployhart and Vandenberg’s (2010) requirements for investigating dynamic theories. The focus of Study 1 was to examine why change in resiliency occurs, and to examine the nature of adverse events that may necessitate the role of resiliency. Study 2, then aimed to examine how resiliency changes over time in response to job loss, but also how change in resiliency can help explain and account for variation in well-being and job search self-efficacy over and above PsyCap. Thus, in terms of Ployhart and Vandenberg’s requirements, Study 1 was positioned to provide evidence for why the change occurs, whereas Study 2 provided evidence for the form of change in resiliency over time, and also the outcomes of change.

**Method**

**Overview**

Study 2 offers an investigation of the trajectory of the resiliency process, but also provides an investigation into the relations between the resiliency trajectories and important outcome variables. Study 1 had required repeated measures before and after a (or series of) challenging event(s). Study 2, on the other hand, involved the assumption that losing one’s job would be considered a significant adversity, and focused on the process of recovery over time, rather than obtaining an assessment of SDT need satisfaction or resiliency before being
laid off. Thus, as the motivations for Study 1 and Study 2 differed, so did the fundamental research design. Accordingly, both Study 1 and Study 2 play a complementary role in the accumulation of knowledge regarding the dynamic nature of resiliency, but offer differing perspectives.

Participants

Partnering with two nation-wide consulting organizations that specialize in outplacement, participation was sought from individuals who had recently been fired (i.e., within the previous 26 weeks [and had not obtained regular, full-time employment by the time of the first survey]). This sample consisted of 111 individuals \( (n_{\text{male}} = 59, 53.2\% \); \( n_{\text{female}} = 50, 45.0\% \); two did not disclose his or her sex), with an average age of 53.05 years \( (SD = 7.46) \). The majority of the sample had obtained at least one university or college degree \( (n = 91, 72.1\% \) ), with many of those \( (n = 35, 31.5\% \) ) having also obtained an advanced degree like a Master’s or Ph.D. (one participant did not disclose their education level; the remainder of participants noted an ‘Other’ education level). The majority of participants had been employed as mid-level \( (n = 29, 26.1\% \) ) or senior managers \( (n = 64, 57.7\% \) ), with front-line supervisors and operational employees comprising the remainder \( (n = 17, 15.3\% \); one participant did not disclose their previous organizational level). Participants had been employed in diverse functional areas (e.g., finance, IT; a breakdown is provided in Table 15). Average tenure on participants’ previous jobs was 3.61 years \( (SD = 3.48) \), and tenure with their previous organization was 6.85 years \( (SD = 7.62) \). Participants had been unemployed for an average of 7.98 weeks \( (SD = 7.23) \) before participating in the Time 1 survey. For 40 participants (36.0\%) it was their first experience with being fired.
Table 15

*Functional Job Areas of Study 2 Participants*

<table>
<thead>
<tr>
<th>Functional Area</th>
<th>Frequency</th>
<th>Proportion (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Finance</td>
<td>21</td>
<td>18.9</td>
</tr>
<tr>
<td>Marketing</td>
<td>14</td>
<td>12.6</td>
</tr>
<tr>
<td>Sales</td>
<td>17</td>
<td>15.3</td>
</tr>
<tr>
<td>Customer Service</td>
<td>3</td>
<td>2.7</td>
</tr>
<tr>
<td>Operations, Production, or Distribution</td>
<td>11</td>
<td>9.9</td>
</tr>
<tr>
<td>Research &amp; Development</td>
<td>3</td>
<td>2.7</td>
</tr>
<tr>
<td>Human Resources</td>
<td>9</td>
<td>8.1</td>
</tr>
<tr>
<td>Information Technology</td>
<td>5</td>
<td>4.5</td>
</tr>
<tr>
<td>Administration</td>
<td>4</td>
<td>3.6</td>
</tr>
<tr>
<td>Other</td>
<td>23</td>
<td>20.7</td>
</tr>
</tbody>
</table>

*Note. n = 111. One participant did not report the functional area of his or her previous job.*
Measures

Psychological Well-Being. The same shortened version of Ryff and Keyes’ (1995; see also Ryff, 1989a, 1989b) PWB measure from van Dierendonck (2005) that was used in Study 1 was also used in Study 2. Similar to Study 1, all PWB items were responded to on a five-point Likert scale anchored by Strongly disagree and Strongly agree at the low and high endpoints, respectively. Reliability estimates for all three measurements can be found in Table 16. The entire set of items can be found in Appendix E.

Job Search Self-Efficacy. JSSE was assessed using items adapted from Judge, Locke, Durham, and Kluger (1998) and Saks and Ashforth (1999). Recently, Liu et al. (2014) used the three items developed by Judge et al., however, Cronbach’s α was relatively modest, with an average estimate of .70. As such, in the current study six additional items from Saks and Ashforth were included. As shown in Table 16, this JSSE measure demonstrated substantially stronger evidence of internal consistency reliability, and in supplementary exploratory factor analyses, the nine items demonstrated a single-factor solution as optimal. The three items adapted from Judge et al. were responded to on a five-point Likert agreement scale anchored by Strongly disagree and Strongly agree, and the six items adapted from Saks and Ashforth were responded to on a five-point Likert confidence scale anchored by Not at all Confident to Totally Confident. An example item from Judge et al. includes “When I make plans about my job search actions, I am certain I can make them work,” and an example item from Saks and Ashforth includes “Impressing interviewers during employment interviews.” The entire set of items can be found in Appendix R.

Resiliency. As in Study 1, McLarnon and Rothstein’s (2013) WRI was also used to assess resiliency in Study 2. Also in keeping with the measures used by Study 1, all WRI items were responded to on a five-point Likert scale anchored by Strongly disagree and
Strongly agree. Cronbach’s α estimates and cross-time correlations for all of the WRI’s eight facet scales across all three measurements can be found in Table 16. The entire set of WRI items can be found in Appendix G.

Psycap. Again, similar to Study 1, the complete set of 24 PsyCap items from Luthans et al. (2007) was assessed in Study 2. As in the usage from Study 1, all PsyCap items were responded to on a five-point Likert scale anchored by Strongly disagree and Strongly agree at the low and high endpoints, respectively. Reliability estimates can be found in Table 16. Five items of the PsyCap’s Resiliency scale can be located in Appendix F.

Procedure

As Study 2 aimed to focus on the trajectory of change in resiliency and its relation to important outcome variables (i.e., JSSE and PWB) three assessment were required. Participants (see Appendix P for ethics approval document) were included on an on-going basis as they were referred from either of the consulting organizations. Outplacement consultants were the first contact point with potential participants, and if any of their clients voiced interest in participation, the consultant forwarded their contact information. Participation was encouraged in exchange for an entry to win one of four Apple iPads that were randomly awarded at the completion of the study. Upon receipt of a potential participant’s contact information, an email containing a link to the Letter of Information and the Time 1 survey was sent.

Subsequent surveys were administered at three-month intervals, so that the first follow-up assessment was administered three months after the initial survey was completed, and the second, and final, follow-up assessment was sent out after an additional three months. This timeline was chosen based on discussions with representatives of the consulting organization, as they indicated that a timeframe of approximately six months was typical of
Table 16

Study 2 Reliability

<table>
<thead>
<tr>
<th>Scale</th>
<th>Cronbach’s α</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Time 1</td>
</tr>
<tr>
<td>Psychological Well-Being</td>
<td>.811</td>
</tr>
<tr>
<td>Job Search Self-Efficacy WRI</td>
<td>.883</td>
</tr>
<tr>
<td>PCA</td>
<td>.789</td>
</tr>
<tr>
<td>PCB</td>
<td>.822</td>
</tr>
<tr>
<td>PCC</td>
<td>.826</td>
</tr>
<tr>
<td>OSR</td>
<td>.951</td>
</tr>
<tr>
<td>IR</td>
<td>.890</td>
</tr>
<tr>
<td>SRPA</td>
<td>.820</td>
</tr>
<tr>
<td>SRPB</td>
<td>.741</td>
</tr>
<tr>
<td>SRPC</td>
<td>.850</td>
</tr>
<tr>
<td>PsyCap</td>
<td>.882</td>
</tr>
</tbody>
</table>

Note. PC-A = Personal Characteristics – Affective; PC-B = Personal Characteristics – Behavioral; PC-C = Personal Characteristics – Cognitive; IR = Initial Response; OSR = Opportunities, Supports, and Resources; SRP-A = Self-Regulatory Processes – Affective; SRP-B = Self-Regulatory Processes – Behavioral; SRP-C = Self-Regulatory Processes – Cognitive. All test-retest reliability coefficients significant at \( p < .01 \).
their clients’ transitions between jobs. Further, recent examinations of the job transition process have been conducted over periods that would suggest six months as a typical timeframe (see Gowan, 2012; Haynie & Shepherd, 2011; Rampell, 2011; Statistics Canada, 2011; Wanberg, 2012; Wanberg, Kanfer, & Banas, 2000; Wanberg, Glomb, & Song, 2005, Wanberg et al., 2010; Wanberg et al., 2012). A research assistant kept detailed records of each participant’s invitation and completion dates so that each participant had equal intervals between assessments. The research assistant was also able to keep the intervals of assessment roughly equal for each participant so there was no need to include time of assessment as a time-varying covariate in subsequent analyses (see Singer & Willett, 2003).

As in Study 1, prior to the administration of the WRI at each timepoint, special instructions were given to each participant, which described a priming scenario so that individuals are able to reflect on the processes involved with ‘bouncing back’ from being fired. The prime was developed in consultations with Drs. Gillian King and Mitchell Rothstein (see Appendix Q).

**Analytical Procedure**

As Study 2 aimed to explore longitudinally-oriented research questions of a substantively different nature than Study 1, a slightly different analytical strategy was required. Initially, I had aimed to use latent growth modeling (LGM; Bentein, Vandenberg, Vandenberghe, & Stinglhamber, 2005; Bollen & Curran, 2006; Chan, 1998; Lance, Vandenberg, & Self, 2000). This analytical method was motivated by S. J. Peterson et al.’s (2011) study of the longitudinal change in PsyCap, and their accompanying estimation of the relation between change in PsyCap and job performance. However, LGMs with three timepoints are linear in nature. Upon completing data collection and based on preliminary descriptive analyses, I determined that across the PWB, JSSE, WRI, and PsyCap measures,
there was a substantial downward trend from Time 1 to Time 2 scores, and then a substantial increase in Time 3 scores from Time 2. Thus, comparing Time 1 to Time 3 scores resulted in a somewhat static presentation of the data, and covered up to two distinct and substantial trajectories. Therefore, I revised the analytical procedure I had originally proposed and aimed to examine change between the resiliency variables and the outcome variables separately across Time 1 to Time 2 assessments, and across Time 2 to Time 3 assessments. This meant that I would use the LDS (McArdle, 2009) approach I used in Study 1.

Thus, the analytical procedure of Study 2 mimics some of the analyses conducted in support of Study 1. As such, there is little need to repeat the technical aspects and parameterization of the LDS models here, and readers are referred back to Study 1 for further details. Also as completed in Study 1, prior to estimating the LDS models, I thoroughly examined the MI of the focal variables across all three timepoints. However, differing from Study 1, after the estimation and derivation of LDS scores for the PWB, JSSE, WRI, and PsyCap variables, hierarchical multiple regression was used to assess the relations between change in the PWB and JSSE variables and change in the WRI and PsyCap variables. Here, I explore the incremental prediction offered by change in the WRI over and above change in the PsyCap variables in the prediction of changes in the PWB and JSSE variables.

**Missing Data.** As noted in Study 1, missing data is often an inherent issue with longitudinal research, and as such, several additional strategies were used in Study 2 over and above those described in relation to Study 1. First, individuals were encouraged to participate in exchange for a chance to win one of four Apple iPads that were to be awarded by lottery at the completion of data collection. Participants were actively reminded of the chance to win an iPad with every invitation to complete a survey. Participants were offered a chance to win with every completed survey (for a maximum of three lottery entries per volunteer). Second,
participants were also sent reminder emails if no survey response was recorded. The first reminder email was sent after three business days of not responding to the invitation. Two additional follow-up emails were then sent at additional three-day intervals, and if still no response was recorded on the survey the participant did not receive any further contact pertaining to the study (except of course if he or she were to win an iPad). Three, FIML missing data methods, in conjunction with Mplus 7.31’s MLR estimator (L. K. Muthén & Muthén, 2015), were used to provide minimally biased parameter estimates.

There was however, a relatively large degree of drop-out for Study 2’s participation rates. In particular, as noted, the Time 1 assessment consisted of 111 participant responses. At the first follow-up assessment three months later, responses could only be solicited from 46 individuals (41.44% of Time 1 participants). Again, this was after having sent three reminder emails to those individuals that did not respond to the request to complete the survey. At the subsequent Time 3 assessment, participation further dropped to 33 responses (29.73% of Time 1 participants; 71.74% of Time 2 participants). Saks et al. (2015) noted a similar level of drop-out (only 20% completed) over the duration of an eight-month survey. Notably, partially completed surveys were relatively rare, in that if an individual entered the survey by in large the entire survey was completed.

Therefore, in light of the advantages of FIML and MLR estimation presented above in Study 1, I used the same techniques in the MI and LDS CFAs of Study 2. As a check on the performance of the FIML methodology here, after the estimation of each CFA model I checked whether the model fit and parameter estimates differed substantially when listwise deletion was invoked (i.e., \( n = 30 \)). In no analysis reported did the parameter or model fit estimates differ appreciably, and thus, even though less than 50% of the sample had completed three measurements it appears that FIML was able to accurately estimate the
parameter values despite the presence of missing data. Moreover, as a check on the guideline of using FIML with up to 50% missing data (see Enders, 2001, 2010; Graham, 2009; Ployhart & Vandenberg, 2010), in Appendices S and T I provide additional support for the efficiency and effectiveness of FIML estimation in Study 2 by examining model fit and parameter estimates of the focal study analyses when using a reduced sample of \( n = 66 \).\(^{10}\) This resulted in being able to take advantage of the full sample size reported at Time 1, because, as in Study 1, when factor scores were saved from the LDS model the sample size was not downwardly biased by missing data. To be clear, the data were not “imputed” in this case, but the parameters of each model were estimated as if data had not been missing. Then, as one of the focal measurement parameters estimated were the latent means of the LDS variables, sample size was preserved to the greatest possible extent when factor scores were exported and saved for use in the subsequent regression analyses. Also, as in Study 1, before proceeding to the main results, I considered the impact of non-random participant drop-out.

As for non-purposeful responding, similar to Study 1 I did not resort to flagging non-purposeful responding by using direct check items (i.e., “Please answer strongly agree to this question”). This was because the surveys were quite short in length (approximately only 15 minutes to complete each survey), and that participants were prompted to participate in exchange for an entry for the iPad lottery. As well, only a trivial portion (\( n = 1; .90\% \)) of participants passed the \( p < .001 \) Mahalanobis distance cut-off, and as such were retained in the sample. Thus, Study 2’s main analyses used a sample size of 111.

**Testing drop-out effects.** To investigate the potential impact of participant drop-out, I tested systematic bias between participants who completed the Time 3 survey and those

\(^{10}\) Participants were excluded in a systematic basis given the time between job loss and the Time 1 survey. Those who had been laid off within 4 weeks comprise the reduced sample of \( n = 66 \), whereas those who had been laid off within 26 weeks are in the initial sample.
who did not. As in Study 1, I assessed the prevalence and potential effects of systematic, or non-random drop-out among participants with four preliminary analyses, which were informed by Goodman and Blum (1996). These involved a logistic regression with the missing status at Time 3 as the dependent, and Time 1’s focal and demographic variables as the predictors. Second, mean differences in the Time 1 variables across those who stayed and who left were assessed using an independent samples $t$-test. Third, differences in variances of the Time 1 variables were examined across the whole sample versus those that stayed till Time 3. Finally, I compared multiple regressions of Time 1 variables, with PWB as the dependent variable, across the whole sample versus those that stayed to complete Time 3.

Appendix U documents the results of all four of these assessments of drop-out effects (see Goodman & Blum, 1996), but in the interest of brevity only the significant effects will be highlighted. According to the logistic regression, Time 1 OSR and education level were associated with non-response at Time 3, $b = -1.298$, $p < .010$, OR = .273, $b = -4.45$, $p < .010$, OR = .641. Thus, with increasing education level and Time 1 OSR scores participants were more likely to have dropped-out by Time 3. No significant mean differences were revealed by the independent samples $t$-test, and thus, means of the demographics and focal variables assessed at Time 1 did not differ significantly across those who responded to all three surveys and those who had dropped out. As well, there were no significant differences in variance estimates between the full sample, and those who responded to the Time 3 survey. Although there were several differences in terms of significant multiple regression coefficients, none were found to be significantly different (Kenny, 1987). Thus, with only evidence presented by the logistic regression, the analyses recommended by Goodman and Blum (1996) predominantly suggested random drop-out during the course of Study 2. However, as noted, since drop-out exceeded 50% of the initial sample, I conducted several
sensitivity analyses to examine the potential biasing effects of this degree of drop-out. These additional analyses will be discussed further in the Limitations.

Results

Descriptives, intercorrelations, and reliability estimates can be found in Tables 17-19.

Longitudinal Confirmatory Factor Analyses

As sample size in Study 2 is more modest than that of Study 1, I place more emphasis on the $\chi^2$ test rendered across nested models associated with longitudinal MI. This is because with a more modest sample size (i.e., $n = 111$, versus $n = 400$ as in Study 1), the $\chi^2$ test is unlikely to signal trivial degrees of misfit (see Kelloway, 1995). As such, I focus on the findings associated with the $\chi^2$ tests of MI, but present the CFI, RMSEA, $\Delta$CFI, and $\Delta$RMSEA estimates for the sake of completion.

As in Study 1, the MI analyses conducted here across all three timepoints were more of a stepping stone, rather than being of a focal research interest, and are presented in detail in Appendix V. Similar to the results presented by Study 1’s LCFAs, the measures used in Study 2 demonstrate evidence of invariance over time. This, as noted, supports the longitudinal validity of each measure, which suggests that each functions and means the same to respondents across timepoints (Chan, 2011).

There were several slight differences between the LCFAs conducted here and the analyses conducted as part of Study 1. For the PsyCap measure, in light of the slightly more modest sample size in Study 2 than Study 1, rather than examine the invariance of the second-order factor model (F. F. Chen, Sousa, & West, 2005; Cheung, 2008; Credé & Harms, 2015), I used a first-order model, in which the observed mean scores for each of the Self-Efficacy, Hope, Resiliency, and Optimism facets were used as indicators of the latent PsyCap
Table 17

Study 2, Time 1 Intercorrelation Matrix

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
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<tbody>
<tr>
<td>1</td>
<td>PWB</td>
<td></td>
<td></td>
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<td></td>
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<tr>
<td>2</td>
<td>JSSE</td>
<td>.568</td>
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<td></td>
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</tr>
<tr>
<td>3</td>
<td>PC-A</td>
<td>.297</td>
<td>.298</td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>PC-B</td>
<td>.244</td>
<td>.132</td>
<td>.149</td>
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<td>5</td>
<td>PC-C</td>
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<td>.264</td>
<td>.284</td>
<td>.201</td>
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<td>6</td>
<td>OSR</td>
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<td>.114</td>
<td>.208</td>
<td>.123</td>
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<td></td>
<td></td>
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<td>7</td>
<td>IR</td>
<td>-0.295</td>
<td>-0.475</td>
<td>-0.260</td>
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SD .378 .655 .629 .460 .602 .807 .863 .594 .533 .651 .376

Note. n = 111. PWB = psychological well-being; JSSE = job search self-efficacy; PC-A = Personal Characteristics – Affective; PC-B = Personal Characteristics – Behavioral; PC-C = Personal Characteristics – Cognitive; IR = Initial Response; OSR = Opportunities, Suppports, and Resources; SRP-A = Self-Regulatory Processes – Affective; SRP-B = Self-Regulatory Processes – Behavioral; SRP-C = Self-Regulatory Processes – Cognitive. Correlations greater than |.19| p < .05, greater than |.25| p < .01.
Table 18

*Study 2, Time 2 Intercorrelation Matrix*

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Note. $n = 46$. PWB = psychological well-being; JSSE = job search self-efficacy; PC-A = Personal Characteristics – Affective; PC-B = Personal Characteristics – Behavioral; PC-C = Personal Characteristics – Cognitive; IR = Initial Response; OSR = Opportunities, Supports, and Resources; SRP-A = Self-Regulatory Processes – Affective; SRP-B = Self-Regulatory Processes – Behavioral; SRP-C = Self-Regulatory Processes – Cognitive. Correlations greater than |.30| $p < .05$, greater than |.38| $p < .01$. 
Table 19

Study 2, Time 3 Intercorrelation Matrix

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Note. $n = 33$. PWB = psychological well-being; JSSE = job search self-efficacy; PC-A = Personal Characteristics – Affective; PC-B = Personal Characteristics – Behavioral; PC-C = Personal Characteristics – Cognitive; IR = Initial Response; OSR = Opportunities, Supports, and Resources; SRP-A = Self-Regulatory Processes – Affective; SRP-B = Self-Regulatory Processes – Behavioral; SRP-C = Self-Regulatory Processes – Cognitive. Correlations greater than $|.35| p < .05$, greater than $|.45| p < .01$. 
variable. This was because the first-order model requires the estimation of fewer parameters, and therefore would help facilitate a more reasonable ratio of sample size-to-number of parameters estimated. As well, the first-order factor model approach was used by S. J. Peterson et al. (2011) in their longitudinal analyses of the PsyCap. As well as following S. J. Peterson et al.’s procedure, this approach is also supported by the recent recommendations of Cole, Perkins, and Zelkowitz (in press), who suggested that homogeneous item parcels (i.e., facet scales) should be used when the latent variable indicated is multidimensional.

As well, given the smaller sample size and the extra timepoint in comparison to Study 1’s analyses, the longitudinal MI of the WRI was examined scale by scale. Thus, with eight constituent scales, I conducted eight separate MI analyses on the WRI to comprehensively investigate the invariance of its psychometric properties over time.

Even in consideration of these procedural differences, several of the analytical steps used in these MI analyses revealed evidence of partial invariance. As introduced, but not invoked in Study 1, partial invariance occurs when equality of any of the model’s parameters cannot be supported (see Flora et al., 2008). Study 2, however, revealed several instances of partial invariance. This occurred in the metric invariance analysis of the WRI’s OSR facet, and in the strict invariance analyses for the PC-A and SRP-C facets of the WRI, the PsyCap, and the PWB measure. Thus, one of the factor loadings associated with one of the item parcels was found to be significantly different over time, and one residual variance from the PC-A, SRP-C, PsyCap, and PWB scales was found to be non-equivalent across timepoints. In all of these cases, however, freeing a single parameter constraint allowed the LCFA models to surpass the $\Delta \chi^2$ test so that invariance was supported. Methodologists have suggested that if invariance is supported for at least two of a latent factor’s indicators then it can be considered invariant (Byrne et al., 1989; Morin et al., 2009; Morin, Moullec et al.,
2011; Sharma et al., 2012; Vandenb,
This was the same method applied in Study 1 to examine Mover-Stayer differences. However, Study 2 looked at change over two timepoints (recall the intended usage of LGM, but was prevented by the non-linear growth), and thus latent difference scores were computed across both Time 1 → Time 2 and Time 2 → Time 3 time lags. Recall that there was a noticeable downward trend from Time 1 to Time 2, and then an upward trend from Time 2 to Time 3, thus necessitating two separate difference scores to accurately map the trajectories of interest. Similar to Study 1’s LDS usage, each LDS model was estimated based on the strict, or at least partially strict, invariance models stemming from the longitudinal MI analyses.

Table 20 provides the model fit indices of all the Time 1 to Time 2 LDS models, and according to the $\chi^2$, CFI, and RMSEA estimates demonstrated reasonably adequate fit to the data. However, the models for the PC-A and SRP-B facets of the WRI demonstrated fit indices that indicate mediocre model fit (i.e., CFI of .850 - .899; T. D. Little, 2013). These modest estimates of model-data correspondence were found despite the PC-A LDS model accounting for the one non-equivalent residual variance discussed earlier. In other words, this PC-A LDS model demonstrated mediocre fit, despite accounting for the non-invariant residual variance found in the previous longitudinal invariance analyses. This was a similar case for the SRP-B facet, which demonstrated full invariance, but demonstrated mediocre LDS fit. Of note, however, the estimates of model fit for the PC-A and SRP-B facets were slightly lower than the other WRI facets during all of the longitudinal invariance analyses, and thus more modest model fit indices was expected at this stage.
Figure 6. Sample of 15 participants’ Personal Characteristics – Affective (top panel), Initial Response (middle panel), and Self-Regulatory Processes – Cognitive (bottom panel) scores over all three timepoints of Study 2.
Table 20

*Time 1 → Time 2 Latent Difference Score Model Fit Summaries*

<table>
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<th>Model</th>
<th>$\chi^2$</th>
<th>$\chi^2_c$</th>
<th>$\chi^2_{df}$</th>
<th>#fp</th>
<th>CFI</th>
<th>RMSEA</th>
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<tr>
<td>PC-A</td>
<td>65.154**</td>
<td>.989</td>
<td>31</td>
<td>23</td>
<td>.862</td>
<td>.100 (.066 - .134)</td>
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<td>32</td>
<td>22</td>
<td>.962</td>
<td>.056 (.000 - .096)</td>
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<td>37.033</td>
<td>1.030</td>
<td>32</td>
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<td>.983</td>
<td>.038 (.000 - .083)</td>
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<td>22</td>
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<td>.081 (.042 - .117)</td>
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<td>62.626**</td>
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<td>25</td>
<td>.949</td>
<td>.103 (.068 - .138)</td>
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<td>22</td>
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<td>.057 (.000 - .097)</td>
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<td>.954</td>
<td>32</td>
<td>22</td>
<td>.877</td>
<td>.102 (.068 - .135)</td>
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<td>23</td>
<td>.949</td>
<td>.080 (.038 - .118)</td>
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<td>47.523*</td>
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<td>32</td>
<td>22</td>
<td>.965</td>
<td>.069 (.017 - .108)</td>
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</table>

*Note.* $\chi^2_c$ = scaling correction factor for $\chi^2$; $df$ = degrees of freedom; #fp = number of parameters estimated in each model; CFI = comparative fit index; RMSEA = root mean square error of approximation, with 90% CIs in parentheses; PC-A = Personal Characteristics – Affective; PC-B = Personal Characteristics – Behavioral; PC-C = Personal Characteristics – Cognitive; IR = Initial Response; OSR = Opportunities, Supports, and Resources; SRP-A = Self-Regulatory Processes – Affective; SRP-B = Self-Regulatory Processes – Behavioral; SRP-C = Self-Regulatory Processes – Cognitive; PWB = psychological well-being; JSSE = jobs search self-efficacy. All LDS models were estimated based on the strict, or partial strict, invariance models, as described in Appendix V. * $p < .05$, ** $p < .01$. 

131
Table 21 provides the model fit indices of all the Time 2 to Time 3 LDS models, and as in the Time 1 to Time 2 models, according to the $\chi^2$, CFI, and RMSEA estimates demonstrated adequate fit to the data. Although different from the Time 1 to Time 2 LDS models, there were also several models that demonstrated potentially mediocre fit for the Time 2 to Time 3 LDS transitions. Here, the PC-B model was found to have a CFI of .866, which is below the .900 cut-off often used to indicate acceptable model fit (i.e., Hu & Bentler, 1999; T. D. Little, 2013). However, as noted above, this CFI value was considered to be in the range of mediocre model fit by T. D. Little (2013), and as such I retained it for further analysis. As well, the Time 2 to Time 3 SRP-A LDS model demonstrated a CFI of .900, suggesting that its model-data fit was right on the cusp of acceptability and may warrant caution in interpreting the following results. Despite these modest estimates of model-data fit, I proceeded with all the Time 1 to Time 2 and Time 2 to Time 3 LDS analyses, and exported scores for each individual’s transitions for use in subsequent multiple regression analyses. However, in light of these modest estimates of model-data fit for some of the focal LDS models, the issue of potentially mediocre fit will be addressed further in the Discussion.

**Power analyses.** More so than Study 1, given the relatively small sample size and relatively large degree of drop-out over time, a consideration of statistical power is necessary. Thus, as the LDS analyses comprise the first component of this Study’s focal analyses, I examined the power of these models to identify the focal latent difference parameters. I accomplished this through two methods. First, I determined the specific estimate of power for each of these LDS models through Satorra and Saris’ (1985) method. Satorra and Saris described the ability to estimate the power of a given parameter by misspecifying the focal parameter and using the LRT to detect the change in the overall model fit given by the misspecification. As degree of misfit indicated by the LRT is sensitive to sample size, Satorra
Table 21

Table 2 → Time 3 Latent Difference Score Model Fit Summaries

<table>
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<th></th>
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<th>(\chi^2) df</th>
<th>#fp</th>
<th>CFI</th>
<th>RMSEA</th>
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<td>.967</td>
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<td>23</td>
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<td>.055 (0.00 - .096)</td>
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<td>22</td>
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<td>55.698**</td>
<td>.976</td>
<td>31</td>
<td>23</td>
<td>.900</td>
<td>.085 (.047 - .121)</td>
</tr>
<tr>
<td>SRP-B</td>
<td>50.695*</td>
<td>1.092</td>
<td>32</td>
<td>22</td>
<td>.935</td>
<td>.073 (.030 - .109)</td>
</tr>
<tr>
<td>SRP-C</td>
<td>29.656</td>
<td>1.031</td>
<td>32</td>
<td>22</td>
<td>1.000</td>
<td>.000 (0.00 - .064)</td>
</tr>
<tr>
<td>PsyCap</td>
<td>62.699**</td>
<td>.856</td>
<td>32</td>
<td>22</td>
<td>.930</td>
<td>.097 (.061 - .132)</td>
</tr>
<tr>
<td>PWB</td>
<td>93.785**</td>
<td>.936</td>
<td>61</td>
<td>29</td>
<td>.910</td>
<td>.072 (.041 - .099)</td>
</tr>
<tr>
<td>JSSE</td>
<td>53.738**</td>
<td>.943</td>
<td>31</td>
<td>23</td>
<td>.944</td>
<td>.084 (.044 - .121)</td>
</tr>
</tbody>
</table>

*Note. \(\chi^2_{c}\) = scaling correction factor for \(\chi^2\); df = degrees of freedom; #fp = number of parameters estimated in each model; CFI = comparative fit index; RMSEA = root mean square error of approximation, with 90% CIs in parentheses. PC-A = Personal Characteristics – Affective; PC-B = Personal Characteristics – Behavioral; PC-C = Personal Characteristics – Cognitive; IR = Initial Response; OSR = Opportunities, Supports, and Resources; SRP-A = Self-Regulatory Processes – Affective; SRP-B = Self-Regulatory Processes – Behavioral; SRP-C = Self-Regulatory Processes – Cognitive; PWB = psychological well-being; JSSE = jobs search self-efficacy. All LDS models were estimated based on the strict, or partial strict, invariance models, as described in Appendix V. * \(p < .05\), ** \(p < .01\).
and Saris’ method allows researchers to estimate power for a focal parameter across a range of sample sizes by manipulating a statistical model’s sample size and maintaining the same degree of misspecification for the focal parameter.

Second, I also examined power through the more general Monte Carlo-based approach described by L. K. Muthén and Muthén (2002). Muthén and Muthén’s method allows for an overall assessment of the power, accuracy, and relative bias of various model parameters at given sample sizes. This method uses a Monte Carlo study to generate data based on a model with parameters fixed at the estimates offered by a normal, freely estimated model to determine the relative accuracy and bias associated with recovering each parameter. Multiple Monte Carlo studies can be run with varying sample sizes to determine bias and accuracy associated with differing sample sizes given a set of parameter values for a particular statistical model. Although both Satorra and Saris’ (1985) and Muthén and Muthén’s method are generalized approaches and are applicable to any structural equation model, in completing these power analyses I considered the recommendations of Sbarra and Allen (2009) who applied LDS methods and subsequently considered the power of their LDS model.

Appendix W details the results of the power analyses from Satorra and Saris’ (1985) method. Appendix X details the results of the power analyses from Muthén and Muthén’s (2002) method. Notably, there were few cases in which the power to detect significant values for the focal parameters of interest (i.e., variance of the LDS variable, factor loadings) were below acceptable cut-offs. In particular, with sufficient power often considered to be .80 or greater (with $\alpha = .05$), according to Satorra and Saris’ method, none of the variances estimates associated with the latent difference variables demonstrated power to be less
than .80. As well, these focal parameters were found to have adequate coverage and low levels of bias from the Monte Carlo method of Muthén and Muthén. A notable advantage of Muthén and Muthén’s method is that it can be programed to include cases that are missing data at various rates across the different variable. As such, the Monte Carlo analyses I programed included the missing data proportions observed by this study to more accurately estimate power and bias given the attrition associated with Study 2. Taken together, these analyses would suggest that these LDS models had sufficient statistical power, and that the latent difference scores retained from each model were minimally biased and represented the true change over time (see Reuter et al., 2010; McArdle, 2009).

Hierarchical Multiple Regressions

Moving towards the test of the hypotheses focal to Study 2, multiple regression was used to explore the relations between change in the WRI facets and longitudinal change in the JSSE and PWB outcome variables. As an extension, hierarchical multiple regression was also used to investigate whether changes in PsyCap provide evidence of incremental variance over and above the WRI. In this regard, the hierarchical multiple regressions were supplemented with relative importance analyses to explore which variables were the most important and reflected the strongest relation with each outcome.

Although the multiple regression analyses took the form of traditional ordinary least square regression (Cohen, Cohen, West, & Aiken, 2003; see e.g., McLarnon & Rothstein, 2013), readers may be less familiar with relative importance techniques, and are further detailed here. Johnson (2000) proposed that as a supplement to multiple regression models,

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11 This was also the case for the results of the power analyses with n = 66. A sample size of 66 is relevant to the later sensitivity analyses conducted to demonstrate the robustness of the main analyses, given the current guidelines and recommendations for FIML usage are in cases with up to 50% missing data has resulted (e.g., Ployhart & Vandenberg, 2010; Enders, 2010; Newman, 2014; recall that $n_{Time 3} = 33$).
the relative importance of each predictor be examined, rather than focus on the regression coefficients. As my coauthors and I stated in O’Neill, McLarnon, Schneider, and Gardner (2014) in our audit on the use of multiple regression in management research, relative weights analysis can help researchers better understand the particular role a specific predictor plays in the presence of more than one predictor. Johnson’s method of deriving relative weights allows researchers to make statements about the relative importance of each variable in predicting the criterion, and avoids the fallacies involved with directly comparing standardized (or unstandardized) regression coefficients (see Tonidandel & LeBreton, 2011; Tonidandel, LeBreton, & Johnson, 2009). As such, I used the analytical tools published by Tonidandel and LeBreton (2015) and implemented in R 3.2.0 (R Core Team, 2015) to supplement Step 2 of these hierarchical multiple regression analyses.

**Psychological Well-Being, Time 1 to Time 2.** The first outcome variable analyzed was PWB and the changes exhibited from Time 1 to Time 2. Table 22 documents the results of this regression. With all eight of the WRI’s facets entered into the first step, the $R^2$ was .302, $p < .01$ ($R^2_{\text{adjusted}} = .242$). In this regression model two of the WRI’s components were found to significantly add to the prediction of Time 1 to Time 2 changes in PWB: PCB and OSR. PCB demonstrated a .276, $p < .01$ regression coefficient, and the regression coefficient associated with OSR was -.321, $p < .01$.

A brief word about interpreting these coefficients may be necessary given that they represent the difference between the Time 1 and Time 2 scores. The LDS models computed the difference scores as Time 2 subtract Time 1. As Time 2 scores were predominantly lower than Time 1, more positive scores rendered by the LDS for the Time 1-Time 2 differences would suggest a smaller decrease over time. Therefore, the positive regression coefficient between the Time 1 $\rightarrow$ Time 2 PWB and PCB scores suggests that the more PWB was
maintained, or even increased modestly, was associated with a greater extent to which PCB levels were maintained. Thus, during the Time 1 to Time 2 transition protecting one’s level of PCB was positively associated with, and added to the prediction of smaller decreases in PWB over time. In other words, for individuals who were more likely to have protected their PCB capacities, their PWB level was also more likely to have been maintained.

The opposite conclusion can be drawn from the negative coefficient involving the Time 1 → Time 2 relation between PWB and OSR. In this case, larger decreases in social support were associated with experiencing less decrease in well-being at Time 2. Thus, individuals that have experienced a greater decrease in support available from close personal relationships were more likely to have maintained their PWB. Although this negative relation may be somewhat counterintuitive, several plausible explanations can still be rendered, and will be discussed later in more detail.

Next, the Time 1 → Time 2 LDS-derived PsyCap scores were added to the regression in the second block. The inclusion of PsyCap resulted in a total model $R^2$ of .333, $p < .01$ ($R^2_{adjusted} = .268$), and an $\Delta R^2 = .031$, $p < .05$ ($\Delta R^2_{adjusted} = .026$). With an emphasis on the adjusted $R^2$ values due to the larger number of WRI than PsyCap predictors (recall that Luthans et al. have recommended using the overall PsyCap score rather than the scores from the self-efficacy, hope, optimism, and resilience facets), this suggests that including the PsyCap can help explain 2.6% more variance in Time 1 → Time 2 PWB changes. This second step in the regression also revealed a significant negative coefficient for PsyCap, $- .205$, $p < .05$. As in the OSR relation discussed previously, this would suggest that a greater decrease in PsyCap across the Time 1 and Time 2 assessments was associated with less change in PWB. As well, the second step in this regression revealed a significant positive
Table 22

Hierarchical Multiple Regression Results for Time 1 → Time 2 PWB on Time 1 → Time 2 WRI and PsyCap Predictors

<table>
<thead>
<tr>
<th></th>
<th>Step 1 Bs</th>
<th>Step 2 Bs</th>
<th>Step 2 RW</th>
<th>Step 2 RW%</th>
</tr>
</thead>
<tbody>
<tr>
<td>PC-A</td>
<td>-.114</td>
<td>-.107</td>
<td>.014</td>
<td>4.056</td>
</tr>
<tr>
<td>PC-B</td>
<td>.276**</td>
<td>.311**</td>
<td>.078</td>
<td>22.980</td>
</tr>
<tr>
<td>PC-C</td>
<td>-.159</td>
<td>-.112</td>
<td>.018</td>
<td>5.169</td>
</tr>
<tr>
<td>IR</td>
<td>-.159</td>
<td>-.187</td>
<td>.042</td>
<td>12.437</td>
</tr>
<tr>
<td>OSR</td>
<td>-.321**</td>
<td>-.291**</td>
<td>.091†</td>
<td>26.769</td>
</tr>
<tr>
<td>SRP-A</td>
<td>-.014</td>
<td>-.004</td>
<td>.002</td>
<td>.617</td>
</tr>
<tr>
<td>SRP-B</td>
<td>-.026</td>
<td>-.085</td>
<td>.014</td>
<td>4.161</td>
</tr>
<tr>
<td>SRP-C</td>
<td>.173</td>
<td>.234*</td>
<td>.063</td>
<td>18.634</td>
</tr>
<tr>
<td>PsyCap</td>
<td></td>
<td>-.205*</td>
<td>.018</td>
<td>5.177</td>
</tr>
</tbody>
</table>

\[ R^2 \quad .302** (.242) \quad .333** (.268) \]
\[ \Delta R^2 \quad .031* (.026) \]

Note. PWB = psychological well-being; WRI = Workplace Resiliency Inventory; PC-A = Personal Characteristics – Affective; PC-B = Personal Characteristics – Behavioral; PC-C = Personal Characteristics – Cognitive; IR = Initial Response; OSR = Opportunities, Supports, and Resources; SRP-A = Self-Regulatory Processes – Affective; SRP-B = Self-Regulatory Processes – Behavioral; SRP-C = Self-Regulatory Processes – Cognitive; RW = raw relative weight, RW% = relative weight rescaled to proportion of model \( R^2 \). Values in parentheses are adjusted \( R^2 \) estimates. Table presents standardized regression coefficients. † Relative weight has a 95% confidence interval that does not include zero. * \( p < .05 \), ** \( p < .01 \).
association between SRP-C and PWB, \( .234, p < .05 \). Such that maintaining one’s cognitive self-regulation over time was related to maintaining well-being at the first follow-up assessment. Finally, the relative weights supplemental analysis suggested that changes in the OSR variable were the most important in adding to the prediction of Time 1 → Time 2 changes in PWB. In particular, OSR was the only variable to demonstrate a relative weight coefficient that was significantly different from zero, \( .091 (95\% \ CI = .02 \text{ - } .21) \), thus suggesting that OSR accounted for 26.77% of the total \( R^2 \).

**Psychological Well-Being, Time 2 to Time 3.** With data from three measurement occasions available, two sets of predictor variable can be utilized in the prediction of the Time 2 → Time 3 outcomes. The first to be examined is how Time 1 → Time 2 transitions may help to predict the Time 2 → Time 3 changes in the PWB. Table 23 documents the results of this regression. The first step, which included the WRI’s eight components resulted in a \( R^2 \) of \( .166, p < .05 \) (\( R^2_{\text{adjusted}} = .095 \)). Two of the WRI’s components were found to significantly add to the prediction of Time 2 to Time 3 changes in PWB. The IR facet demonstrated a \( B = .225, p < .05 \), and the SRP-B facet was found to have a \( B = .290, p < .05 \). Thus, the stronger one’s reaction was to the experience of job loss at the first follow-up as compared to the initial assessment, the less decrease experienced in PWB. As well, with more positive increase in Time 1 to Time 2 behavioral self-regulation, PWB was also more likely to be protected or increased. Thus, over time, the greater control over one’s ineffective behaviors the more positive well-being is likely to be at the second follow-up as compared to the first follow-up.

In the second step of the hierarchical regression, there was no evidence to support the incremental validity of the Time 1 → Time 2 changes in PsyCap adding to the prediction of the Time 2 → Time 3 changes in PWB. The \( \Delta R^2 \) was \( .000, ns \), and the regression coefficient
associated with PsyCap was .018, ns. This would suggest that the Time 1 → Time 2 changes in PsyCap do not add to the prediction of the Time 2 → Time 3 changes in PWB. As well, the relative weights supplement did not provide any evidence of statistically significant results, so all of the relative weights coefficients included zero in their 95% CIs. Thus, even though the regression of Time 2 → Time 3 PWB on Time 1 → Time 2 SRP-B accounted for 26.04% of the total variance explained in PWB, it did not reach levels associated with statistical significance.

Although the cross-lagged relations between the Time 1 → Time 2 predictors and Time 2 → Time 3 outcomes is advantageous from a common method bias view (see Podsakoff et al., 2003), I also deemed it informative to examine relations between transitions of the Time 2 → Time 3 and the Time 2 → Time 3 outcomes. Thus, the last regression using PWB is presented in Table 24 and shows that the $R^2$ of the Time 2 → Time 3 changes in PWB was $0.335, p < .01$ ($R^2_{\text{adjusted}} = 0.278$). Inasmuch, 33.5% of the variance in PWB changes can be accounted for by changes in the eight WRI components. In this first step of the regression the PC-A, IR, and SRP-B components were found to significantly add to prediction. PC-A demonstrated a regression coefficient of $-0.351, p < .01$, and suggested that the more substantially Time 3 PC-A has decreased as compared to Time 2 scores, the greater PWB has been maintained across the same timeframe. IR was found to significantly add to the regression with $B = -0.403, p < .01$, suggesting that, in contrast to the Time 1 → Time 2 prediction, the weaker one’s reaction to the experience of job loss at Time 3 as compared to Time 2, the better one’s well-being is over the same timepoints. SRP-B was also found to significantly add to prediction, with a $B = -0.213, p < .01$. This might suggest that the less one is exercising behavioral self-regulation at Time 3 as compared to Time 2, the greater the chance one’s well-being is likely to have increased or been maintained.
Table 23

Hierarchical Multiple Regression Results for Time 2 → Time 3 PWB on Time 1 → Time 2 WRI and PsyCap Predictors

<table>
<thead>
<tr>
<th></th>
<th>Step 1 Bs</th>
<th>Step 2 Bs</th>
<th>Step 2 RW</th>
<th>Step 2 RW%</th>
</tr>
</thead>
<tbody>
<tr>
<td>PC-A</td>
<td>.193</td>
<td>.192</td>
<td>.035</td>
<td>20.523</td>
</tr>
<tr>
<td>PC-B</td>
<td>-.125</td>
<td>-.128</td>
<td>.006</td>
<td>3.679</td>
</tr>
<tr>
<td>PC-C</td>
<td>-.151</td>
<td>-.155</td>
<td>.013</td>
<td>7.881</td>
</tr>
<tr>
<td>IR</td>
<td>.225*</td>
<td>.228*</td>
<td>.038</td>
<td>22.241</td>
</tr>
<tr>
<td>OSR</td>
<td>.085</td>
<td>.082</td>
<td>.014</td>
<td>8.230</td>
</tr>
<tr>
<td>SRP-A</td>
<td>-.079</td>
<td>-.080</td>
<td>.005</td>
<td>2.709</td>
</tr>
<tr>
<td>SRP-B</td>
<td>.290*</td>
<td>.295*</td>
<td>.044</td>
<td>26.040</td>
</tr>
<tr>
<td>SRP-C</td>
<td>.201</td>
<td>.196</td>
<td>.013</td>
<td>7.670</td>
</tr>
<tr>
<td>PsyCap</td>
<td></td>
<td></td>
<td>.018</td>
<td>1.026</td>
</tr>
</tbody>
</table>

\[ R^2 \quad .166^* (.095) \quad .166^* (.085) \]

\[ \Delta R^2 \quad .000 (-.009) \]

Note. PWB = psychological well-being; WRI = Workplace Resiliency Inventory; PC-A = Personal Characteristics – Affective; PC-B = Personal Characteristics – Behavioral; PC-C = Personal Characteristics – Cognitive; IR = Initial Response; OSR = Opportunities, Supports, and Resources; SRP-A = Self-Regulatory Processes – Affective; SRP-B = Self-Regulatory Processes – Behavioral; SRP-C = Self-Regulatory Processes – Cognitive; RW = raw relative weight, RW% = relative weight rescaled to proportion of model $R^2$. Values in parentheses are adjusted $R^2$ estimates. Table presents standardized regression coefficients. † Relative weight has a 95% confidence interval that does not include zero. * $p < .05$, ** $p < .01$. 
Subsequently, adding the Time 2 → Time 3 changes in PsyCap as a predictor of Time 2 → Time 3 changes in PWB significantly added to the variance explained in PWB, $R^2 = .392$, $p < .01$, $R^2_{\text{adjusted}} = .333$, with $\Delta R^2 = .057$, $p < .01$, $\Delta R^2_{\text{adjusted}} = .055$. In this step, both the PC-A and IR coefficients maintained their level of significance and direction, however the regression coefficient for SRP-B was reduced to -.110 and was no longer statistically significant. On the other hand, the contribution of PsyCap was found to be significant with $B = .286$, $p < .01$. Thus, the greater one’s PsyCap is at Time 3 as compared to Time 2 positively relates to greater PWB at Time 3 than Time 2. As well, in this second step the relative weights for PC-A, IR, and PsyCap contained 95% CIs that excluded zero. Of particular interest, the contribution of IR to the prediction of Time 2 → Time 3 PWB was found to be most important, as changes in IR were found to alone account for 37.06% of the variance accounted for by all nine of the predictors included in the second step of this hierarchical regression. PsyCap and PC-A accounted for 28.76% and 20.11% of the model $R^2$, respectively. As such, in terms of importance, change in IR was the most important predictor, followed by changes in PsyCap and PC-A.

Thus, across the Time 1 → Time 2 and Time 2 → Time 3 changes in PWB, the resiliency components tapped by the WRI were able to account for a significant proportion of variance. These results, therefore, support Hypothesis 2.1. As well, PsyCap demonstrated evidence of incremental validity in the Time 1 → Time 2 regression of PWB on Time 1 to Time 2 changes in PsyCap, and in the regression of Time 2 → Time 3 PWB on Time 2 to Time 3 changes in PsyCap.
Table 24

Hierarchical Multiple Regression Results for Time 2 → Time 3 PWB on Time 2 → Time 3 WRI and PsyCap Predictors

<table>
<thead>
<tr>
<th></th>
<th>Step 1 Bs</th>
<th>Step 2 Bs</th>
<th>Step 2 RW</th>
<th>Step 2 RW%</th>
</tr>
</thead>
<tbody>
<tr>
<td>PC-A</td>
<td>-.351**</td>
<td>-.264**</td>
<td>.079†</td>
<td>20.106</td>
</tr>
<tr>
<td>PC-B</td>
<td>.073</td>
<td>.023</td>
<td>.002</td>
<td>.481</td>
</tr>
<tr>
<td>PC-C</td>
<td>.154</td>
<td>.125</td>
<td>.015</td>
<td>3.859</td>
</tr>
<tr>
<td>IR</td>
<td>-.403**</td>
<td>-.371**</td>
<td>.145†</td>
<td>37.057</td>
</tr>
<tr>
<td>OSR</td>
<td>-.108</td>
<td>-.082</td>
<td>.013</td>
<td>3.355</td>
</tr>
<tr>
<td>SRP-A</td>
<td>.095</td>
<td>-.013</td>
<td>.006</td>
<td>1.500</td>
</tr>
<tr>
<td>SRP-B</td>
<td>-.213**</td>
<td>-.110</td>
<td>.012</td>
<td>3.177</td>
</tr>
<tr>
<td>SRP-C</td>
<td>.004</td>
<td>-.053</td>
<td>.007</td>
<td>1.703</td>
</tr>
<tr>
<td>PsyCap</td>
<td></td>
<td>.286**</td>
<td>.113†</td>
<td>28.761</td>
</tr>
</tbody>
</table>

\[ R^2 \quad .335** (.278) \quad .392** (.333) \]

\[ ΔR^2 \quad .057** (.055) \]

*Note.* PWB = psychological well-being; WRI = Workplace Resiliency Inventory; PC-A = Personal Characteristics – Affective; PC-B = Personal Characteristics – Behavioral; PC-C = Personal Characteristics – Cognitive; IR = Initial Response; OSR = Opportunities, Supports, and Resources; SRP-A = Self-Regulatory Processes – Affective; SRP-B = Self-Regulatory Processes – Behavioral; SRP-C = Self-Regulatory Processes – Cognitive; RW = raw relative weight, RW% = relative weight rescaled to proportion of model \( R^2 \). Values in parentheses are adjusted \( R^2 \) estimates. Table presents standardized regression coefficients. † Relative weight has a 95% confidence interval that does not include zero.

* * p < .05, ** p < .01.
**Job Search Self-Efficacy, Time 1 to Time 2.** The second outcome this study examined was JSSE. In the same manner as PWB, three multiple regressions were used to explore the relations between changes in JSSE and changes in the WRI and PsyCap predictors. Table 25 shows the results of the hierarchical multiple regressions for the Time 1 → Time 2 changes in JSSE on the Time 1 → Time 2 changes in the WRI and PsyCap. The first step, which only included the eight WRI facets resulted in an $R^2 = .203$, $p < .01$ ($R^2_{\text{adjusted}} = .135$). Included in this step was one significant regression coefficient for PC-B. Here, the regression coefficient was .227, $p < .05$, and suggested that to a greater extent that PC-B is maintained or built over the Time 1 to Time 2 assessments, the more likely one would have maintained or increased his or her sense of efficacy for undertaking a successful job search.

Adding the Time 1 → Time 2 PsyCap variable did not significant add to the prediction of Time 1 → Time 2 changes in JSSE as both the $\Delta R^2$ value, .010 ($\Delta R^2_{\text{adjusted}} = .002$) and PsyCap’s regression coefficient, .119, were not statistically significant. Thus, in this case, there was no evidence of PsyCap’s incremental validity. Then, applying the relative weights supplements to the step 2 regression revealed that changes in PC-B was the most important predictor of changes in JSSE. In particular, changes in PC-B accounted for 33.22% of the variance accounted for by the total model, $R^2 = .214$, $p < .01$.

**Job Search Self-Efficacy, Time 2 to Time 3.** In contrast to the previous sets of findings involving prediction of Time 1 → Time 2 changes in JSSE, and the regressions of Time 2 → Time 3 PWB on the Time 1 → Time 2 predictors, none of the results obtained for the regression of Time 2 → Time 3 changes in JSSE on the Time 1 → Time 2 predictors were significant. In this case, as shown in Table 26, none of the $R^2$ values, nor $\Delta R^2$ estimates reached the $p < .05$ level. As well, none of the regression coefficients, in either step, or their respective relative weights, could be deemed as statistically different from zero. Thus, neither
Table 25

*Hierarchical Multiple Regression Results for Time 1 → Time 2 JSSE on Time 1 → Time 2 WRI and PsyCap Predictors*

<table>
<thead>
<tr>
<th></th>
<th>Step 1 Bs</th>
<th>Step 2 Bs</th>
<th>Step 2 RW</th>
<th>Step 2 RW%</th>
</tr>
</thead>
<tbody>
<tr>
<td>PC-A</td>
<td>-.008</td>
<td>-.012</td>
<td>.000</td>
<td>.188</td>
</tr>
<tr>
<td>PC-B</td>
<td>.227*</td>
<td>.208*</td>
<td>.071†</td>
<td>33.219</td>
</tr>
<tr>
<td>PC-C</td>
<td>.116</td>
<td>.089</td>
<td>.027</td>
<td>12.599</td>
</tr>
<tr>
<td>IR</td>
<td>-.108</td>
<td>-.092</td>
<td>.017</td>
<td>8.092</td>
</tr>
<tr>
<td>OSR</td>
<td>-.080</td>
<td>-.098</td>
<td>.004</td>
<td>2.039</td>
</tr>
<tr>
<td>SRP-A</td>
<td>-.018</td>
<td>-.024</td>
<td>.001</td>
<td>.333</td>
</tr>
<tr>
<td>SRP-B</td>
<td>.201</td>
<td>.235</td>
<td>.059</td>
<td>27.344</td>
</tr>
<tr>
<td>SRP-C</td>
<td>.121</td>
<td>.085</td>
<td>.014</td>
<td>6.528</td>
</tr>
<tr>
<td>PsyCap</td>
<td></td>
<td>.119</td>
<td>.021</td>
<td>9.656</td>
</tr>
</tbody>
</table>

\[ R^2 = .203** (.135) \quad \text{.214** (.137)} \]

\[ \Delta R^2 = .010 (.002) \]

*Note. JSSE = job search self-efficacy; WRI = Workplace Resiliency Inventory; PC-A = Personal Characteristics – Affective; PC-B = Personal Characteristics – Behavioral; PC-C = Personal Characteristics – Cognitive; IR = Initial Response; OSR = Opportunities, Supports, and Resources; SRP-A = Self-Regulatory Processes – Affective; SRP-B = Self-Regulatory Processes – Behavioral; SRP-C = Self-Regulatory Processes – Cognitive; RW = raw relative weight, RW% = relative weight rescaled to proportion of model \( R^2 \). Values in parentheses are adjusted \( R^2 \) estimates. Table presents standardized regression coefficients. † Relative weight has a 95% confidence interval that does not include zero. * \( p < .05 \), ** \( p < .01 \).
the Time 1 → Time 2 changes in the WRI or PsyCap variables was able to add to the prediction and explanation of Time 2 → Time 3 changes in JSSE.

On the other hand, there were several noteworthy results to report from the regression of the Time 2 → Time 3 changes in JSSE on the Time 2 → Time 3 predictors, as displayed by Table 27. In the first step of the hierarchical regression $R^2 = .205, p < .01$, $R^2_{adjusted} = .136$, suggesting that the WRI components can account for a significant proportion of variance in Time 2 to Time 3 changes in JSSE. Moreover, OSR was found to significantly contribute to the regression equation, with a $B = -.262, p < .05$. Similar to the regression of Time 1 → Time 2 PWB on Time 1 → Time 2 predictors, this negative relation would suggest larger decreases in social support were associated with experiencing less decrease in self-efficacy related to the search for new employment. Thus, an individual that has experienced a greater decrease in support available from close personal relationships were more likely to have maintained his or her JSSE.

With the addition of Time 2 → Time 3 changes in PsyCap into the second step of this regression, the model $R^2$ increased to $.244, p < .01$, $R^2_{adjusted} = .170$, which equals a $\Delta R^2$ of $.039, p < .05$, $\Delta R^2_{adjusted} = .034$. Thus, including the changes in PsyCap can account for an additional 3.4% of the variance explained in Time 2 → Time 3 changes in JSSE. Furthermore, in this second step three regression coefficients were found to differ significantly from zero: OSR, SRP-B, and PsyCap. OSR demonstrated a coefficient of -.240, $p < .05$, of which can be accompanied by a similar interpretation as rendered above for the finding involving the first step of the regression. On the other hand, the Time 2 → Time 3 changes in SRP-B were now found to significantly add to prediction with a regression weight of $.254, p < .05$. Thus, the higher Time 3 SRP-B scores were as compared to Time 2 scores,
Table 26

*Hierarchical Multiple Regression Results for Time 2 $\rightarrow$ Time 3 JSSE on Time 1 $\rightarrow$ Time 2 WRI and PsyCap Predictors*

<table>
<thead>
<tr>
<th></th>
<th>Step 1 Bs</th>
<th>Step 2 Bs</th>
<th>Step 2 RW</th>
<th>Step 2 RW%</th>
</tr>
</thead>
<tbody>
<tr>
<td>PC-A</td>
<td>.085</td>
<td>.088</td>
<td>.004</td>
<td>3.836</td>
</tr>
<tr>
<td>PC-B</td>
<td>.007</td>
<td>.022</td>
<td>.002</td>
<td>2.055</td>
</tr>
<tr>
<td>PC-C</td>
<td>.065</td>
<td>.086</td>
<td>.003</td>
<td>2.936</td>
</tr>
<tr>
<td>IR</td>
<td>-.004</td>
<td>-.016</td>
<td>.001</td>
<td>1.590</td>
</tr>
<tr>
<td>OSR</td>
<td>.100</td>
<td>.113</td>
<td>.004</td>
<td>4.568</td>
</tr>
<tr>
<td>SRP-A</td>
<td>-.083</td>
<td>-.078</td>
<td>.004</td>
<td>4.112</td>
</tr>
<tr>
<td>SRP-B</td>
<td>-.264</td>
<td>-.291</td>
<td>.048</td>
<td>52.464</td>
</tr>
<tr>
<td>SRP-C</td>
<td>.155</td>
<td>.183</td>
<td>.025</td>
<td>26.567</td>
</tr>
<tr>
<td>PsyCap</td>
<td></td>
<td>-.093</td>
<td>.002</td>
<td>1.873</td>
</tr>
</tbody>
</table>

$R^2$ .086 (.007) .092 (.003)

$\Delta R^2$ .006 (-.004)

*Note. JSSE = job search self-efficacy; WRI = Workplace Resiliency Inventory; PC-A = Personal Characteristics – Affective; PC-B = Personal Characteristics – Behavioral; PC-C = Personal Characteristics – Cognitive; IR = Initial Response; OSR = Opportunities, Supports, and Resources; SRP-A = Self-Regulatory Processes – Affective; SRP-B = Self-Regulatory Processes – Behavioral; SRP-C = Self-Regulatory Processes – Cognitive; RW = raw relative weight, RW% = relative weight rescaled to proportion of model $R^2$. Values in parentheses are adjusted $R^2$ estimates. Table presents standardized regression coefficients. \(\dagger\) Relative weight has a 95% confidence interval that does not include zero. * $p < .05$, ** $p < .01$.\*
Table 27

**Hierarchical Multiple Regression Results for Time 2 → Time 3 JSSE on Time 2 → Time 3 WRI and PsyCap Predictors**

<table>
<thead>
<tr>
<th></th>
<th>Step 1 Bs</th>
<th>Step 2 Bs</th>
<th>Step 2 RW</th>
<th>Step 2 RW%</th>
</tr>
</thead>
<tbody>
<tr>
<td>PC-A</td>
<td>-.063</td>
<td>.009</td>
<td>.001</td>
<td>.549</td>
</tr>
<tr>
<td>PC-B</td>
<td>.098</td>
<td>.056</td>
<td>.011</td>
<td>4.611</td>
</tr>
<tr>
<td>PC-C</td>
<td>.019</td>
<td>-.006</td>
<td>.002</td>
<td>.673</td>
</tr>
<tr>
<td>IR</td>
<td>-.170</td>
<td>-.143</td>
<td>.036</td>
<td>14.662</td>
</tr>
<tr>
<td>OSR</td>
<td>-.262*</td>
<td>-.240*</td>
<td>.067</td>
<td>27.652</td>
</tr>
<tr>
<td>SRP-A</td>
<td>.152</td>
<td>.062</td>
<td>.011</td>
<td>4.506</td>
</tr>
<tr>
<td>SRP-B</td>
<td>.169</td>
<td>.254*</td>
<td>.052†</td>
<td>21.269</td>
</tr>
<tr>
<td>SRP-C</td>
<td>.089</td>
<td>.042</td>
<td>.011</td>
<td>4.378</td>
</tr>
<tr>
<td>PsyCap</td>
<td></td>
<td>.238*</td>
<td>.053</td>
<td>21.699</td>
</tr>
</tbody>
</table>

\[ R^2 \quad .205** (.136) \quad .244** (.170) \]
\[ \Delta R^2 \quad .039* (.034) \]

*Note.* JSSE = job search self-efficacy; WRI = Workplace Resiliency Inventory; PC-A = Personal Characteristics – Affective; PC-B = Personal Characteristics – Behavioral; PC-C = Personal Characteristics – Cognitive; IR = Initial Response; OSR = Opportunities, Supports, and Resources; SRP-A = Self-Regulatory Processes – Affective; SRP-B = Self-Regulatory Processes – Behavioral; SRP-C = Self-Regulatory Processes – Cognitive; RW = raw relative weight, RW% = relative weight rescaled to proportion of model \( R^2 \). Values in parentheses are adjusted \( R^2 \) estimates. Table presents standardized regression coefficients. † Relative weight has a 95% confidence interval that does not include zero. * \( p < .05 \), ** \( p < .01 \).
the higher the positive change in JSSE over the same time lag. Additionally, the regression coefficient associated with PsyCap was found to be statistically stronger than zero, $B = .238$, $p < .05$. Therefore, the greater one’s PsyCap is at Time 3 as compared to Time 2 positively relates to greater JSSE at Time 3 than Time 2. As well, the SRP-B’s role in the second step of this regression provided evidence of a significant relative weight coefficient. In particular, SRP-B had the only significant relative weight, .052 (95% CI = .00 -.21). Thus, although the relative weights for OSR and PsyCap were larger, their confidence intervals included zero, suggesting that the coefficients were not significantly different from zero and that SRP-B’s role was the most important in predicting Time 2 → Time 3 JSSE.

Except in the cross-lagged regression of Time 2 → Time 3 changes in JSSE on the Time 1 → Time 2 changes in the WRI components and PsyCap, the resiliency variables were able to account for a significant proportion of variance in changes in JSSE. This, therefore supports Hypothesis 2.2. PsyCap was also provided evidence of incremental validity, but only in the hierarchical regression of Time 2 → Time 3 JSSE on Time 2 to Time 3 changes in PsyCap.

These results conclude the Results for Study 2, and by way of summarizing these findings, I can suggest that changes in the WRI components and PsyCap help predict changes in the PWB and JSSE outcomes. These findings of significant relations provided evidence to support hypotheses forwarded on the association between the components of resiliency and the two important outcome variables that occupied the focus of Study 2.

**Power analyses.** As in the LDS analyses used to derive scores for use in these multiple regressions, given the somewhat limited sample size, one might be wary of the significant results presented. As such, following these regressions I also examined power of the $F$-test associated with the $R^2$ and $\Delta R^2$ statistics to detect significant estimates. As shown
in Appendix Y, for most of the analyses involving the WRI variables in the first block power was at adequate levels (i.e., greater than .80). However, in the regression of Time 2 → Time 3 JSSE on Time 1 to Time 2 changes in the WRI, which was non-significant, power was estimated to be only .525. As well, power to detect a significant change in $R^2$ due to the inclusion of PsyCap was only found to be greater than .80 in the regression of Time 2 → Time 3 PWB on Time 2 → Time 3 changes in the predictors. In the other hierarchical regressions, power was generally quite low. This issue will be further discussed in the Limitations. However, given general rules of thumb ranging from 10 cases per predictor variable to $50 + 8m$, where $m$ is the number of predictors (Tabachnick & Fidell, 2007), the results shown here do suggest a reasonable level of power associated with these hierarchical multiple regressions.

**Sensitivity analyses.** As attrition in Study 2 exceeded the guidelines on using FIML to recover unbiased parameter estimates in longitudinal models with up to 50% of missing data lost through MCAR and/or MAR mechanisms (see Enders, 2010; Graham, 2009; Ployhart & Vandenberg, 2010), I examined the possibility of differential results had the current sample exhibited missingness between Time 1 and Time 3 of 50%. In other words, I re-ran the main analyses of Study 2 using a reduced sample of $n = 66$. This meant that at Time 1 there were 66 full cases, and then at Time 2 and Time 3, respectively, the sample sizes described in the main results, $n = 46$, and $n = 33$. With an $n$ of 33 at Time 3, an $n$ of 66 at Time 1 would result in a total attrition of 50%.

To reduce the sample size of Time 1 to 66 from 111, I considered the lag between the experience of job loss and the Time 1 survey. Rather than considering all possible cases, I only examined those individuals who had been laid off within four weeks prior to completing the Time 1 survey. Weeks unemployed before participating in the Time 1 survey was also
unrelated to a non-response on the Time 3 survey \((b = .018, p = .538, \text{OR} = 1.018)\), therefore it was not systematically related to missingness, but functions as a theoretically sound criteria for reducing sample size. I suggest this is an ideal cut-off for reducing the sample size in the interest of these sensitivity analyses so that less time has passed between job loss and the Time 1 survey and that the job loss experience, and the resulting attitudes, behaviors, and thoughts, may be more immediately relevant to participants.

In completing these sensitivity analyses, I followed the same procedure as described above. First I examined the longitudinal MI of the focal constructs. Second, using the strict, or partially strict, invariance analyses, I examined the fit of the LDS model and exported scores associated with the Time 1 → Time 2 and Time 2 → Time 3 changes in each construct. Then using the exported LDS scores, I examined the multivariate relations between the WRI facets, PsyCap, and the two outcomes, PWB and JSSE using hierarchical multiple regression. As supplements to these sensitivity analyses I also produced power estimates for the LDS models using Satorra and Saris’ (1985) method (see Appendix W), and also examined power of the hierarchical multiple regressions (see Appendix X). Additionally, I examined the MI of the longitudinal WRI, PWB, and PsyCap measures across the samples involved in Study 1 and Study 2. In completing this assessment of invariance I was able to demonstrate that the parameter estimates, and factor scores rendered, differed in only trivial degrees across estimates that were derived from the Study 2 sample only, and on those derived from MI models that were equated to the much larger sample involved in Study 1. In what follows, I only highlight important findings and refer readers to the associated Appendices.

First, MI was demonstrated in a very similar manner in the reduced sample, as in the full sample. Strikingly, the same pattern of invariance assessments was rendered across each analysis in the reduced sample. In other words, in each of the longitudinal CFAs, the same
pattern of model fit, and partial invariance, was found in the reduced sample as was described above for the full sample. The model fit results are presented in Appendix S, scale by scale, and mimic the results, particularly in terms of if, and when, each stage of the invariance testing failed the $\Delta \chi^2$ test. Thus, the results of the longitudinal MI assessments do not differ in substance across the full sample, and that provided by a sample with $n = 66$, which corresponds to the allowable missingness for FIML estimation, as recommended by Ployhart and Vandenberg (2010; see also Enders, 2010; Kam et al., in press; Newman, 2014).

Second, referring back to Appendices W and X, which contained the estimates of power to estimate significant variance components of the latent difference scores derived from the strict, or partially strict, MI models, the LDS models generally had adequate power (i.e., above .80) to identify significant estimates. The power associated with the variance of the PC-A difference was estimated to be .821 with a sample size of 66, which was the lowest estimate rendered. Thus, all the power estimates shown were above the conventional cut-off of .80. Notably, these are the same estimates of power for both the Time 1 $\rightarrow$ Time 2 and Time 2 $\rightarrow$ Time 3 changes because all LDS models were estimated with all three timepoints, and thus the misspecification of the LDS variance (to zero) equally impacted the Time 1 $\rightarrow$ Time 2 and Time 2 $\rightarrow$ Time 3 models even though the exported factor scores would have differed.

Third, using the exported factor scores from the previous LDS analyses using the reduced sample, I examined the multivariate relations between the changes in the WRI components and the PsyCap as predictors of change in PWB and JSSE. Although there are some differences in terms of what was deemed significant, according to the $\alpha = .05$ convention, the parameter estimates rendered were often fairly similar between the results of the full sample and those associated with the reduced sample. In particular, as detailed in the
Tables in Appendix T, in the regression of the Time 1 → Time 2 PWB on the Time 1 → Time 2 predictors, PCB and OSR were still found to be significant, in the positive and negative directions, respectively. On the other hand, the inclusion of PsyCap in the second block was found not to contribute significantly to the regression by way of the $\Delta R^2$ estimate and the coefficient associated with PsyCap. Likewise, the coefficient associated with SRP-C was not found to be significant. However, these now non-significant estimates were not drastically different from the convention $p < .05$ level, with the $\Delta R^2$ and PsyCap coefficient $p = .132$, and the $p$-value for SRP-C being .077.

Minor differences also emerged in the Time 2 → Time 3 PWB regression on the Time 1 → Time 2 predictors. First, the $R^2$ estimate in the reduced sample was not significant, whereas the in the full sample it was. However, the estimates were fairly close, .166 versus .211, respectively. In the regressions involving the reduced sample, PC-A and SRP-B were found to contribute significantly. In the full sample IR and SRP-B were found to be significant, but PC-A did not contribute to the prediction of PWB. This is the only relation that emerged in the reduced sample that was not presented in the full sample.

In the Time 2 → Time 3 PWB regression on the Time 2 → Time 3 predictors, all the conclusions drawn from statistically significant estimates were identical between the full sample and the reduced sample. Likewise, in the Time 2 → Time 3 JSSE regression on the Time 1 → Time 2 predictors there were no differences in results. However, in this regression there were no significant findings derived from the full sample. In the Time 1 → Time 2 JSSE regression on the Time 1 → Time 2 predictors there were also no substantial differences except that the significance of the $R^2$ estimate was not significant in the reduced sample. However, the coefficient associated with PC-B was significant in both the full and reduced analyses.
Finally, in the Time 2 → Time 3 JSSE regression on the Time 2 → Time 3 predictors, $R^2$ estimate was not significant in the reduced sample, but did not differ substantially from the significant proportion of variance accounted for in the full sample (.197 versus .205, respectively). One on hand, the OSR coefficient was found to be significant in both the full and reduced samples, but on the other hand, in the reduced sample the $\Delta R^2$, the PsyCap coefficient, and the coefficient associated with SRP-B in the second block were not significant.

These differences, in general, boil down to a reduction in sample size. The differences seen here in what was and what was not significant were primarily associated with sample size and the smaller standard errors associated with the larger number of participants in the full sample. Whether or not the full sample size was used versus one that maintained a 50% level of attrition would have only resulted in fewer conclusions and inferences drawn regarding the incremental role of PsyCap, and also the contribution to the prediction of Time 2 → Time 3 PWB from Time 1 → Time 2 PC-A.

Finally, I developed longitudinal MI models that used a multi-group approach and incorporated the data from Study 1 and Study 2. By doing this, the parameter estimates associated with latent variable variances and factor loadings, and therefore factor scores, would be equated across both samples. This provided a robust method of deriving scores for the reduced sample in Study 2 for comparison against scores from the full sample. As shown in Appendix Z, correlations between latent factor scores from the LDS models using the reduced sample (see earlier MI and power analyses) and MI analyses across timepoints and studies are quite high, average $r = .927$, and range from $r = .745$ to .995.
Discussion

This component of the Discussion is predominantly relevant to the findings of Study 2. A subsequent section will provide a General Discussion and will aim to integrate and provide a complementary perspective on the findings from Study 1 and Study 2. As for Study 2’s Discussion, the remainder of this section is broken-down into several subsections. First I will review the evidence presented for the longitudinal validity of the WRI, next I will discuss the nature of the trajectories of change observed for the WRI components, as well as the observed changes over time in the PWB and JSSE outcome variables. In the subsequent two sections of this Discussion I will review the nature of the relations between the longitudinal changes in the resiliency variables and longitudinal changes in the outcome variables that received support in Study 2. Finally, I will highlight several Limitations that readers should consider when weighing the findings and evidence presented by Study 2.

Longitudinal Validity

Study 1 provided a considerable amount of evidence to support longitudinal validity of the WRI and PsyCap, as well as the SDT and PWB measures used. Study 2 replicated and extended the support of the WRI’s and PsyCap’s longitudinal validity evidence. Specifically, in comparison to Study 1, Study 2 offered evidence to further support of longitudinal validity by assessing these constructs with an additional time point, and by assessing these constructs over longer duration time lags. Thus, Study 2 rendered additional evidence to support propositions that the psychometric properties of the WRI are maintained over time. Moreover, as noted in Study 1, this evidence does not preclude the possibility of intra-individual changes over time, but is often considered a benchmark for longitudinal researchers to have demonstrated, and provides the support necessary to enable accurate comparisons and interpretations of change in the focal constructs over time.
The interpretation and explicit implications of each step in the MI analyses conducted follow that presented in Appendix K and will not be repeated here. What I aim to highlight here instead, are the minor differences that emerged from Study 2’s MI analyses as compared to Study 1’s. From Study 1’s analyses I concluded there was little, if any, evidence to suggest measurement non-invariance. I supported this given the numerical guidelines recommended by F. F. Chen (2007), Cheung and Rensvold (2002), and Sass (2011), who recommended examining changes in the CFI and RMSEA estimates across the various MI steps.

The PC-B, PC-C, IR, SRP-B, and SRP-C facets of the WRI, along with the JSSE outcome variable demonstrated full invariance of their respective longitudinal measurement models. In other words, I was able to apply all of the necessary restrictions specified by measurement invariance on each measure’s factor loadings, parcel intercepts, residual variances, and factor variances without significantly impacting model fit. As noted in relation to Study 1’s findings, this evidence provides compelling support for the longitudinal validity of these measures.

On the other hand, evidence of partial invariance was revealed for the PC-A, OSR, and SRP-C facets of the WRI, and for the PsyCap and PWB measures. Although this may seem like substantially weaker evidence for the longitudinal validity of these measures, many methodologists have suggested that evidence of partial invariance is no less persuasive than full invariance (e.g., Byrne et al., 1989; Flora et al., 2008; Morin, Morizot et al., 2009; Morin, Moullec et al., 2011; Sharma et al., 2012; Vandenberg, 2002). This is because the general consensus from these methodologists is that even evidence to support partial metric or partial strict invariance is strong enough to facilitate accurate comparisons and interpretations of change over time or across groups. Thus, the partial metric invariance evidence for the OSR facet of the WRI, and the partial strict invariance evidence for the PC-A and SRP-C facets of
the WRI, PsyCap, and PWB still allow for accurate conclusions to be drawn across time. In other words, the evidence to support only partial invariance of these measures does not impact the practical meaning of invariance over time, and will not impact any of the inferences drawn about the constructs over time. Thus, the evidence of full invariance, partial metric invariance, and partial strict invariance presented by Study 2 supports the longitudinal validity of the WRI, as well as the longitudinal validity of the PsyCap measure and the PWB and JSSE outcome measures.

**Trajectories of Change**

In light of the plots of resiliency scores over time and the evidence obtained from the MI analyses on the equivalence of the latent means, it was obvious that the majority of trajectories of change were nonlinear in nature. This was the case for the constructs assessed by the WRI, as well as the trajectories for the PsyCap measures, though not all were to a statistically significant degree. All of the focal measures demonstrated a downward trend in mean scores at Time 2 as compared to Time 1, and then a subsequent upwards trend at Time 3 as compared to Time 2. This was particularly salient for the findings involving the factor mean invariance tests of PC-A, IR, SRP-A, and SRP-C of the WRI, all of which demonstrated statistically significant non-invariance (see Appendix V).

Thus, it appeared that the nature of the trajectories was qualitatively distinct during each time lag (i.e., Time 1 → Time 2 and Time 2 → Time 3). This suggested that the trajectories, of all of the focal constructs, was inherently non-linear, and was not amenable to linear modeling. In light of this evidence on non-linear trajectories uncovered in the current study, I adopted an ad hoc piecewise growth model, in which I treated each transition separately.
As such, rather than providing a unified model of change over time, I continued my examination of the trajectory of change over time by considering the discontinuous nature of the trajectories. Specifically, and will be discussed in further detail below, I examined associations between change observed in the Time 1 → Time 2 resiliency predictors (WRI and PsyCap variables) and change observed in the Time 1 → Time 2 PWB and JSSE outcome variables. As well, I examined how the magnitude of early changes (Time 1 → Time 2) in the resiliency variables related to later changes (Time 2 → Time 3) outcome variables, and associations between both Time 2 → Time 3 predictor and outcome variables.

As this was the first study attempting to document changes in the WRI over an extended period, the longitudinal analyses were somewhat of an exploratory nature. I did, however, recover considerable evidence of a consistent pattern of nonlinear trajectories over time, which is noteworthy in and of itself. The WRI components and the PsyCap, as well as the PWB and JSSE outcomes, demonstrated decreases in mean scores from Time 1 to Time 2, and then an increase from Time 2 and Time 3. Thus, it appears that in the initial phase after the experience of losing one’s job there is a substantial downward trend in one’s resiliency, PsyCap, well-being, and job search efficacy. On the other hand, after having reached an apparent low point approximately three and a half months after getting fired, resiliency, PsyCap, well-being, and job search efficacy scores increase and begin to show improvement and recovery. Accordingly, the Time 2 assessment might be associated with a turning point at which the trajectory of individuals’ resiliency, well-being, and job search self-efficacy changed. In other words, during the Time 1 to Time 2 lag trajectories of change were predominantly negative in nature and exhibited a downward trend. During the Time 2 to Time 3 lag the trajectories of change were positive and characterized by increased scores. So up until about three and a half months following losing one’s job one can expect to
experience a decrease in resiliency as well as one’s well-being and job search competence. Over the next three months though, resiliency, well-being, and job search efficacy can be expected to increase. Thus, following the experience of job loss, individuals can expect to experience multiple, non-linear trajectories of change over time.

Although it is interesting to note the pattern of resiliency, well-being, and JSSE scores over time after the experience of job loss, the current research isn’t in a position to inform the literature on what experience or event may be associated with that turning point. The previous literature informed the current research by noting the negative ways in which job loss impacted individuals. In particular, as reviewed earlier, job loss is related to lower well-being and mental health (McKee-Ryan et al., 2005; Paul & Moser, 2009; Wanberg, 2012). Thus, it seems that these effects are seen in the time lag between job loss and about three and a half months past job loss. After this time lag, well-being and competence begin to recover. Based on this, it is conceivable that during the turning point observed around Time 2 is where individuals begin to recover from his or her depressive symptoms and recover from the profound negative effects of job loss. This turning point may simply be associated with allowing enough time to pass to reduce the salience of losing one’s job, but may also be associated with a more active process in that an individual needs to get over the job loss and needs to get back on his or her proverbial feet. However, the current study is only able to present evidence to support the presence of this turning point as indicated by the initial negative trajectory and subsequent positive trajectory. Future research will be required to take a more nuanced perspective to investigate and uncover when this turning point occurs, and what might influence its occurrence so that it may potentially be expedited.

The research on trajectories of change, whether it focuses on changes in well-being, job search self-efficacy, or the components of resiliency, will need to be followed-up with
additional targeted investigations and explorations. In particular future research will need to include more tests of the presence of linear and nonlinear growth trajectories, and also of relations between growth trajectories and moderators of the observed trajectories. As in my initial propositions, LGM would be very suitable for these research endeavors. Although I was unable to apply LGM in the current study due to the non-linear trajectories observed across three timepoints, non-linear LGM would be possible with a minimum of four timepoints. Specifically, with an additional timepoint, a quadratic latent slope variable could have been specified to model the overall curve illustrated by the initial downward trend and subsequent upward trend (e.g., Diallo, Morin, & Parker, 2014). As well, with five timepoints a two-part or piecewise growth model that specified two distinct linear slope factors (one acting across the first three timepoints and a second influencing the latter timepoints) could have modeled the discontinuous trajectories seen here (e.g., Kohli & Harring, 2013; Xu, Blozis, & Vandewater, 2014). Unfortunately however, obtaining any additional timepoints was not feasible with the sample involved in the current study.

Of note though, LGM, whether it represents a linear trajectory or any variety of non-linear trajectories, requires evidence of measurement invariance to ensure that measurement of the focal constructs has not shifted over time. This would, therefore, render the results of the current study necessary in setting the precedent available for future research (see Keefer, Holden, & Parker, 2013). In particular, with the evidence of longitudinal validity and longitudinal measurement invariance presented, the current study establishes the prerequisite conditions that will enable future research to examine these more advanced analyses.

Following from the exploration of the trajectories of change, and the finding that change over time in the resiliency components and the PWB and JSSE outcomes was predominantly non-linear, I applied the LDS approach (McArdle, 2009) to derive scores of
all of the focal variables in a piecewise manner. Then, I examined relations between change, as implied by the LDS-derived scores, in each of focal predictor and outcome variables.

**Associations Between Change in Resiliency and Change in PWB**

In all three analyses, the changes in the resiliency predictors were able to account for a statistically significant proportion of variance in changes in the PWB outcome. In particular, when discussing the adjusted $R^2$ values, the Time 1 → Time 2 predictors accounted for 26.8% and 8.5% of the variance in the Time 1 → Time 2 and Time 2 → Time 3 changes in PWB, respectively. Additionally, the Time 2 → Time 3 predictors accounted for 33.3% of the variance in the Time 2 → Time 3 changes in PWB. Thus, as a set, the WRI components and the PsyCap variables can account for a substantial amount of variation in changes in well-being.

**PsyCap.** With a focus on the role of PsyCap, in the Time 1 → Time 2 PWB regression, PsyCap demonstrated a significant negative regression coefficient, and accounted for an additional 2.6% of the variance in PWB changes. Given the decrease in PWB from Time 1 to Time 2, the negative relation suggested that greater PWB decreases are related to maintaining or conserving one’s PsyCap resources. Thus, to the greater extent that an individual experiences a decrease in PsyCap from Time 1 to Time 2, the less substantial the accompanying decrease in PWB experienced. This might suggest that the hardship encountered following job loss might actually help to mitigate PsyCap resources lost over time, although during the same timeframe well-being is decreasing. In other words, the greater the decrease from Time 1 to Time 2 in PsyCap, the lower the decrease in well-being experienced. In this case, PsyCap may mitigate further PWB decreases over time, over and above the resiliency components assessed by the WRI. Thus, over the early time lag, as PsyCap resources are expended (see S. J. Peterson et al., 2011; Hobfoll, 1989), the decrease
in well-being associated with losing one’s job is reduced. This provides support for results of
S. J. Peterson et al. in that PsyCap levels may decrease over time after a challenging event, or
a series of challenging events, as an individual may be using their personal resources to
maintain or restore well-being.

In the prediction of Time 2 → Time 3 PWB, Time 1 → Time 2 PsyCap did not
provide any evidence of incremental validity, and in this case the total variance accounted for
was driven by the WRI components. Thus, in contrast to the previously discussed relation,
Time 1 → Time 2 changes in PsyCap are not related to Time 2 → Time 3 changes in well-
being. Thus, changes in PsyCap experienced early in the career transition process do not
relate to changes and recovery in PWB in the latter stages of one’s career transition.
Combined with the previous relation discussed, this suggests that PsyCap functions as a
personal resource in a complex manner. In particular, although PsyCap may indeed play a
role in predicting well-being, it does over a short time frame. In other words, PsyCap
resources developed or available early on during one’s experience of job loss do not play a
role in influencing later changes in well-being. Whereas, PsyCap seems more likely to have
an influence over the same time frame in which changes are experienced in well-being. This
is because PsyCap also demonstrated evidence of incremental validity and a significant
regression coefficient in the regression between Time 2 → Time 3 changes in PWB and
Time 2 → Time 3 changes in the resiliency variables (see Table 24). However, the opposite
direction of relation was found, in that PsyCap now had a positive relation to changes in
PWB. Therefore, as PWB was increasing during the Time 2 to Time 3 lag, PsyCap was also
increasing, such that a greater increase in PsyCap experienced was related to a greater
increase in PWB. Thus, as PWB was increasing, approximately three and a half months after
losing one’s job, PsyCap levels also demonstrated increase.
Resiliency components tapped by the WRI. The WRI’s components, on the other hand, generally demonstrated stronger multivariate relations with PWB. This was evidenced by the relative weights supplement, and in additional supplementary analyses the WRI demonstrated incremental validity over and above PsyCap in each PWB regression. Thus, the facets of resiliency tapped by the WRI demonstrated stronger relations with changes in PWB than PsyCap.

In the regression of Time 1 $\rightarrow$ Time 2 changes in PWB on the Time 1 $\rightarrow$ Time 2 WRI components the regression coefficients for PC-B and OSR emerged as significantly different from zero. The relation between PC-B and PWB was found to be positive, and the relation between OSR and PWB was found to be negative. Again, given the decreasing levels of PWB over the Time 1 to Time 2 timeframe, the PC-B relation suggested that smaller decreases in PC-B were associated with smaller decreases in PWB. Thus, individuals who experienced smaller decreases in their PC-B levels also experienced a lesser decrease in well-being. PC-B taps one’s sense of agency and personal control, those individuals that can better maintain a sense of internal locus of control during the early experience of job loss are better able to maintain well-being. Thus, being able to maintain one’s sense of being in control over the current situation, despite experiencing adversity, is associated with being able to more highly maintain well-being.

The negative relation between the Time 1 and Time 2 changes in PWB and OSR is somewhat more complex. The negative association suggested that larger decreases in social support were related to smaller decreases in well-being. This is somewhat counterintuitive as individuals who have substantially less social support in the middle of their career transition were more likely to have a smaller decrease in well-being. One potential explanation is that the individual has recognized that they no longer have the personal connections and
relationships from the past workplace available to him or her. In this sense, they have come to terms with the loss of social support from previous colleagues, and have accurately reported they have fewer social resources available. Thus, rather than continuing to think that there is an abundance of social support available in one’s environment, those that have reported less availability of social support may be better able to rely on others, outside of the previous workplace, who can play a supportive role. Alternatively, this negative relation might suggest a benefit for individuals that chose to ‘go it alone.’ In this case, individuals may choose to rely on his- or herself during the early experiences of job loss, and consider it a personal challenge to successfully navigate the career transition process, rather than involving and relying on others for support, and don’t dwell on the past.

The relations that added significantly to the prediction of changes in PWB changed somewhat when the cross-lagged analyses were considered. When the Time 1 → Time 2 WRI changes are used as predictors of Time 2 → Time 3 changes in PWB the IR and SRP-B facets demonstrated significant relations. As noted, the IR relation suggests that the stronger one’s reaction to job loss is at Time 2 as compared to Time 1 the less decrease experienced in well-being. This, in keeping with the theme broached above, can suggest a coming to terms with the experience of job loss. Although one might consider a lessening impact of job loss to be advantageous over time, those individuals who noted substantially stronger reactions to job loss at follow-up might have come to terms with how serious losing one’s job was. Individuals that reported stronger IR levels at follow-up may have been more likely to recognize the substantial impact losing one’s job had on their livelihood, and in that recognition the individuals were not blind to the adversity being faced, thus helping to better maintain well-being.
As for the relation demonstrated between SRP-B and PWB over the same time lags, those who had been able to exercise higher behavioral self-regulation at Time 2 than Time 1 were more likely to have experienced less decrease in PWB. Thus, if one is able to think through actions and follow plans accordingly, then it is more likely that PWB will be positively influenced. Sticking to plans, and maintaining a long-term perspective, rather than indulging for short term gains during the early stage of one’s career transition is related to more highly recovering and rebuilding well-being during the latter stage of the experience of job loss. In light of these counterintuitive findings, it may be worthwhile for readers to consider the intrapersonal volatility that may accompany these Time 1 to Time 2 changes. In particular, individuals are likely dealing with a substantial amount of stress and may not be able to effectively navigate the early stages of one’s career transition.

Lastly, in the regression of Time 2 → Time 3 changes in PWB on Time 2 → Time 3 changes in the WRI components, IR was again found to contribute significantly to prediction, in addition to PC-A. As well, if just the WRI components were considered, without the added influence of PsyCap, SR-B was found to add to the prediction of PWB changes from Time 2 to Time 3. Providing further evidence for the notion of a turning point, change experienced in IR now relates negatively to changes in PWB. This suggests that the experience of being laid off is not as impactful at this stage, and that one’s (adverse) response to job loss has weakened substantially. As well, the relation between IR and PWB at this stage may suggest that an individual is ‘getting over’ being fired, where reflecting upon the actual experience of being fired and the events that may have led up to it are not seen as negative or adverse as they had been at Time 2. Thus, individuals that report a weaker IR at Time 3 as compared to Time 2 are more likely to have higher well-being over the same interval.
The relation between PC-A and PWB may suggest a slightly different process at work. The indicated negative relation suggested that the weaker Time 3 PC-A was in comparison to Time 2, the greater the Time 2 to Time 3 change in PWB. In other words, an increase in PC-A over the Time 2 → Time 3 interval was associated with a decrease in PWB over the same timeframe. Thus, as well-being is finally increasing in the Time 2 → Time 3 interval individuals should not be striving to rebuild and maintain their affective protective factors. Doing so might be spreading the individual too thin, so that personal resources are being recovered at the continued expense of well-being. This finding is in line with propositions of information processing theory, which posits that individuals draw upon a potentially finite set of cognitive resources (Pelled, 1996; de Wit, Jehn, & Scheepers, 2013). Thus, rebuilding one’s personal resources limited the ability to simultaneously recover well-being. The results of Study 1 suggested that individuals may have prioritized rebuilding PsyCap over the WRI’s protective resources, but in this case the results suggested that PC-A may be the focus of growth and recovery, rather than PWB. Thus, individuals may attempt to rebuild their personal resources, as theorized by COR (Hobfoll, 1989), rather than the outcome of resource attainment (i.e., well-being). This makes sense given the timeline involved. Approximately after six months post-job loss, an individual would be getting back on the job market (particularly given the recommendations of the outplacement consultants, who generally suggest to abstain from the market for about six months to work on one’s competencies and prepare for a new career). Thus, by the Time 3 assessment, individuals are likely readying themselves to get back on the job market, and with greater protective factors one would likely experience greater well-being at a subsequent timepoint. Future research, will however be needed to further substantiate this point.
This rationalization makes additional sense in light of the relation between PWB and SRP-B. Excluding the role of PsyCap, as in the first step of the hierarchical regression, SRP-B demonstrated a significant negative relation with Time 2 → Time 3 changes in PWB. This relation would suggest that as SRP-B builds at Time 3 as compared to Time 2, it is at the expense of also increasing PWB. Thus, by six months after the experience of job loss, it may not be a benefit to exercise more behavioral self-regulation because at this point, one needs to be active in exploring any available opportunities for new a new job. In other words, the time for cautious exploration of job options is over and it is up to the individual to explore any and all opportunities available. Thus, decreasing the amount of control exercised over one’s behavior would likely benefit the actual search for new job. However, reducing one’s behavioral self-regulation in relation to kick starting the search for new employment comes at the expense of increasing well-being. It stands to reason that as an individual embarks on their job hunt, the difficulty of obtaining new employment, especially that which is at a level comparable to one’s previous employment, may dawn on that individual, thereby reducing their well-being. Although somewhat counterintuitive, it may be possible that as SRP-B increases to help cope with the job search process, PWB decreases because of the related stress experienced. However, future research, perhaps with an additional assessment after obtaining new employment, will be needed to further disentangle this relation.

There is a caveat with the relation between changes in SRP-B and PWB though, in that the probability that it differs significantly from zero decreases when PsyCap is added to the regression model, or when the individual relation between Time 2 → Time 3 changes in SRP-B and Time 2 → Time 3 changes in PWB is examined, \( r = -0.092, p = .354 \). Thus, this relation only achieves a level of significance when only the components of the WRI and the comprehensive model of resiliency it taps are considered.
**Associations between Change in Resiliency and Change in JSSE**

As in the PWB regressions, the analyses involving the job search self-efficacy variable were also conducted across three possible combinations of regression: Time 1 → Time 2 changes in the resiliency predictors was used to account for variance in the Time 1 → Time 2 and Time 2 → Time 3 changes experienced in JSSE. In contrast to the PWB regressions, the WRI components and the PsyCap were only able to account for a significant proportion of variance in JSSE when the regressions used the same interval for the predictors as the outcomes. In the regression of the Time 2 → Time 3 changes in JSSE on the Time 1 → Time 2 predictors none of regression coefficients, the $R^2$ estimates associated with each step, nor the $\Delta R^2$ associated with the inclusion of PsyCap were determined to be significant. Accordingly, this portion of the Discussion only examines the findings resulting from regressions that used changes in predictors and the JSSE that were assessed across the same interval.

In the regression of Time 1 → Time 2 changes in JSSE on the Time 1 → Time 2 changes in the resiliency components showed a significant proportion of variance accounted for. The coefficient for PC-B was positive and significant, which suggested that PC-B added significantly to the prediction of JSSE. As this is a similar finding from the Time 1 → Time 2 PWB regression the interpretation of this relation follows that which was discussed above. The positive relation suggested that the greater Time 2 PC-B scores were in comparison to Time 1 would be associated with greater Time 2 JSSE scores at Time 1. However, given the general downward trend in Time 2 scores as compared to Time 1, the more highly one was able to report a Time 2 PC-B score that was at the same level of the Time 1 score the more likely JSSE would demonstrate this same pattern, namely scores at Time 2 that were as high as Time 1 scores. Thus, individuals who experienced smaller decreases in their PC-B levels
also experienced a lesser decrease in their JSSE scores. Therefore, those who can maintain their sense of agency and personal control during the early stages of the job loss experience would be likely to also maintain their sense of efficacy for searching for a new job. In this way, maintaining a sense of control over the current situation, despite it being one of adversity, is associated with being able to approach the search for new employment with more efficacy and confidence.

Adding PsyCap to the regression of Time 1 to Time 2 JSSE did not result in a significant change in the $R^2$, nor any substantive changes in the regression coefficients already discussed. Thus, PsyCap did not present any evidence of incremental validity in the prediction of JSSE over the Time 1 $\rightarrow$ Time 2 interval.

Turning now to the regression of Time 2 $\rightarrow$ Time 3 changes in JSSE on changes across the Time 2 $\rightarrow$ Time 3 interval for the resiliency predictors, in the first step the WRI components accounted for 13.6% of the variance in JSSE. Although this is similar $R^2$ to the first step in the previous analysis, PC-B was not found to contribute significantly, but OSR was. In this case, also similar to the regression of Time 1 $\rightarrow$ Time 2 changes in PWB on the Time 1 $\rightarrow$ Time 2 WRI components, OSR was found to contribute negatively to prediction. This negative relation suggested that larger decreases in social support at Time 3 as compared to Time 2 were related to similar or smaller JSSE scores across the same interval. As in the previous OSR relation discussed, this may be a somewhat counterintuitive finding, as this denotes that individuals with less social support during the latter stages of their career transition maintained a greater level of JSSE, which to reiterate, is a proximal variable highly associated with job search success (Liu et al., 2014). At this point of one’s career transition, one is likely conducting many networking activities, and although this may increase the quantity of social support, the support is unlikely as meaningful as the support a significant
other or close friend would be able to offer. This networking, though integral for conducting one’s job search, may be more superficial in nature than that required to maintain one’s sense of confidence and efficacy in the job search, and therefore seems to play a somewhat undermining role. Alternatively, this negative relation might suggest that too much social support can challenge one’s confidence because an individual may be presented with an array of opinions (and opportunities) that is too varied or contradictory to help maintain or boost one’s job search confidence. Although this may provide evidence for the benevolence of individuals trying to help an individual obtain adequate employment, this might be a ‘too much of a good thing’ effect, where worse outcomes are seen in relation to improving social support. This would constitute fertile ground for future research.

As noted in the Results section, with the addition of Time 2 → Time 3 changes in PsyCap into the second step of this regression PsyCap was found to significantly add to the prediction of JSSE and demonstrated incremental validity. Here, PsyCap demonstrated a positive regression coefficient with changes in JSSE, and suggested that if PsyCap increased from Time 2 to Time 3, JSSE would experience an associated increase as well. Thus, developing and increasing one’s PsyCap resources, which take the form of hope, optimism, a generalized form of self-efficacy, and resilience, one would likely feel more confident in the search for new employment. Therefore, at this stage in the career transition process, it may be worthwhile undergoing a training program to help develop and build the resources tapped by the PsyCap construct, as any increase from the mid-point of the career transition would likely accompany an increase in JSSE.

It is also notable that in the second step of this regression the relation between JSSE and SRP-B became statistically significant with the inclusion of PsyCap. Thus, when the role of PsyCap is included (and partialed out from JSSE and SRP-B) then the relation between
SRP-B and JSSE is positive and significantly different from zero. This relation suggests that individuals who have increased their usage of behavioural self-regulatory mechanisms during the Time 2 to Time 3 interval may have also experienced an increase in their job search confidence. Thus, individuals who have maintained and increased their planfulness and self-discipline would likely see an increase in their confidence for finding new employment. Therefore if one continues to control ineffective behaviours and manage one’s impulses in favor of striving for long-term goals while undergoing the search for new employment, one is likely to demonstrate greater self-efficacy in the job hunt, and will likely be more successful in the search for new employment. There is also a caveat with this relation, in that it stems from the combined influence of SRP-B and PsyCap (and the other WRI facets). Thus, there is a significant additive effect for both SRP-B and PsyCap in that both, together, contribute positively to increases experienced in JSSE during the latter stages of one’s job search.

**Summary of findings.** Before concluding the discussion of Study 2 with several limitations that should be considered, it may be of interest to acknowledge the specific components found by Study 2 that reflect the positive nature of the resiliency process and relate to achieving desirable outcomes during the career transition process. In the prediction of short-term outcomes (i.e., Time 1 → Time 2 changes in PWB and JSSE) changes in one’s behavioral personal characteristics, social support, cognitive self-regulation, and PsyCap were most likely to impact obtaining positive outcomes. In the prediction of long-term outcomes (Time 2 → Time 3 changes in PWB and JSSE) changes in one’s initial response to getting fired, behavioral self-regulation, affective personal characteristics, social support, and PsyCap were most likely to influence obtaining desirable outcomes during the career transition process.
Limitations of Study 2

There are several limitations that readers may wish to be aware of when weighing the evidence presented by the current study. The current study was able to capitalize on data collected at three separate timepoints. However, although this presents a strong advantage over typical cross-sectional and correlational studies, it does not facilitate assumptions and inferences of causality. Thus, throughout the above Results and accompanying Discussion I have refrained from concluding that, for example, changes in resiliency result in changes in well-being. Instead, I have aimed to provide readers with the evidence that may support an association, without direct causal implications, despite referring to the components of resiliency as predictors and the well-being and job search self-efficacy variables as outcomes. Such inferences would only be possible through the use of rigorous experimental, rather than correlational, research methods.

Although the current study’s use of a longitudinal design presents a significant advantage over cross-sectional designs however, its usage is not without its limitations. Although the time lag between assessments was informed by multiple sources (i.e., Gowan, 2012; Haynie & Shepherd, 2011; Rampell, 2011; Statistics Canada, 2011; Wanberg, 2012; as well as the consultants at the outplace firm that assisted with the current research) that suggested a three-month interval between assessments would be optimal, future research should aim to examine trajectories of change over shorter intervals. In fact, a very recent study by Dormann & Griffin (2015) suggested that the timeframes commonly used in longitudinal research are too long to accurately estimate the trajectories of change over time and the relations between constructs as they change over time. This may indeed be the case in the current study, where the measurement occasions applied, despite being well-informed
prior to data collection, were not sensitive enough to capture the hypothesized within-person deviations or change over time.

Another limitation may be presented by comparing the results of the current study on the trajectory of PsyCap with the findings of S. J. Peterson et al. (2011). As noted in the introduction, S. J. Peterson et al. conducted a longitudinal study on the growth and change in PsyCap over time. Using latent growth modeling, they uncovered evidence for a significant downward linear trend in PsyCap scores over time. Notably, S. J. Peterson et al.’s study followed individuals over the same timeframe as the current study (approximately six months), and also assessed participants at three occasions. Thus, it would have stood to reason that the same type of trajectory would have been uncovered by the current study.

However, the experiences of participants over the duration of the studies may be responsible for the resulting differences in the trajectories of change. As I noted in the introduction, S. J. Peterson et al. suggested that the linear downward trajectory of PsyCap over time might have been due to the fact that participants were continually facing adversity and constantly drawing upon their PsyCap resources without having a chance to grow their resources through an intervention during a continually challenging period at work. On the other hand, participants in the current study faced a single adverse event when they were laid off. Thus, while initially drawing upon their PsyCap resources and continuing to do so throughout the entire duration of the study, at about the three-month mark after firing, termed the turning point, PsyCap levels began increasing. This gives rise to a two-part trajectory of change in that the initial portion is negative, but the second portion is positive. Thus, the nature of the experiences of the current study’s participants presents a direct comparison to the findings of S. J. Peterson et al.
This issue of differences in trajectories may also be further amplified by the modest fit of several of the LDS models used here. Recall that I used McArdle’s (2009) LDS approach to derive difference scores between the Time 1 and Time 2 assessments and Time 2 and Time 3 assessments to examine change over time. The statistical software used (Mplus 7.31 [L. K. Muthén & Muthén, 2015] in this case) to evaluate the LDS models provides estimates of model-data fit as it is CFA-based. For most of the LDS analyses fit was better than the rules of thumb used to evaluate mode acceptability (i.e., CFI > .90 = adequate fit, CFI > .95 = strong fit; Hu & Bentler, 1999). However, fit for the LDS models for the WRI’s PC-A and SRP-B facets at the Time 1 → Time 2 interval were lower than .90. As well, for the Time 2 → Time 3 interval, the model fit estimates for the WRI’s PC-B component was lower than .90. Therefore, as the model fit of these LDS is somewhat lower than the rules of thumb dictate (.862, .877, and .866, respectively) then the subsequent results using these scores in the hierarchical multiple regressions may be suspect. Nevertheless, the degree of misfit is fairly minimal, and as such, would be unlikely to substantially alter the results reported throughout this study.

Perhaps most critically, however, are the issues of sample size and attrition associated with Study 2. Although I aimed to maintain as high a level of participation over time as possible by keeping the survey relatively brief, only using three timepoints, sending the participants three reminder emails if a survey was not completed, and by encouraging participation in exchange for a chance to win one of four iPads, participant drop-outs were unavoidable. In fact, the current study presents a greater proportion of complete data points as compared to a recent study by Saks et al. (2015) who were also interested in exploring the job search process over a similar time lag. Saks et al. study used two measurement occasions, separated by eight months, and resulted in a total of 20% complete cases at the final survey.
In contrast, the current study obtained complete data from approximately 30% of the Time 1 participants. Since missing data would be a concern for nearly all longitudinal research designs, I had aimed to use Mplus’ (L. K. Muthén & Muthén, 2015) robust maximum likelihood estimator in conjunction with FIML methods to help maximize sample size (Enders, 2001, 2010; Kam et al., in press). Thus, the analyses and results reported were not downwardly biased by listwise or pairwise deletion due to missing data. I was able to briefly highlight this previously, as the LCFA parameter or model fit estimates did not differ appreciably across analyses run with listwise deletion (i.e., only those cases with all three complete data points were used) and analyses relying upon the FIML technique. It appeared, therefore, that FIML was able to recover the missing data points lost through MCAR and MAR missing data mechanisms relatively well even though less than 50% of the sample had completed all three measurements. However, future research should endeavor to replicate and extend the current research with a larger sample size in effort to enhance the generalizability of the current study’s findings. A larger sample size, in general, and with a greater proportion of the sample completing all of the required longitudinal measures would help increase confidence in researchers’ longitudinal inferences.

Moreover, in the assessment of association between missing at Time 3 and the data collected at Time 1, I highlighted the role of education and OSR as predicting missingness. In particular, the higher one’s education level, and the greater one’s social support the less likely a participant would respond to the request to complete the Time 3 survey. Thus, the systematic dropout regarding education and social support may be of some concern. However, the dropout may not have impacted the substantive results, as these differences did not translate into any substantial mean or variance differences, nor did they impact the nature of the relations between the focal variables.
On the other hand, these significant relations to drop-out are interesting in their own right, in that those individuals with greater levels of social support and those with higher levels of education were more likely to drop-out of Study 2. This may not be overly surprising, however, given the findings of Anseel, Lievens, Schollaert, and Choragwicka (2010), which documented the incidence that samples of executive-level personnel were more likely to suffer from low survey response rates. As executives are likely highly educated, the finding that education is positively related with drop-out corresponds to the low response rates from executives.

As low sample size, and, in some cases, modest estimates of statistical power, may have impacted this study’s findings, one should be considerate and cautious of these limitations before applying the findings to a new sample. I would strongly advocate for continued research into the longitudinal relations between well-being, job search efficacy, resiliency, and PsyCap before firm conclusions and practical recommendations are offered. Although this research has uncovered some insights into the trajectories of well-being and resiliency over time after the experience of job loss, future researchers would be well-advised to replicate the current study with a larger, more diverse sample, which may be less impacted by participant attrition.

One last concern, revolving around the generalizability of the current study’s findings is that the sample predominantly comprised individuals previously holding upper management positions. The career transition and job search processes may not be the same as for individuals predominantly of a lower rank. Individuals occupying the lower ranks, such as front line employees or operational personnel likely wouldn’t have the flexibility for as long duration transition, nor have the need for such a long duration because they would not identify as strongly with their previous jobs. This is not to say that resiliency would be
unlikely to play a role in lower level employees’ career transitions, but that the nature of the relations would likely be different. As such, and in keeping with the earlier Discussion on the nature of the trajectories over time, future research should investigate the same research questions that have motivated this study with a more diverse sample of individuals who have been laid off. This research, if completed, may equip the literature with a more general, comprehensive, and nuanced perspective on nature of the career transition process and also the role resiliency plays after the experience of job loss.

**Conclusion**

Study 2 offered an exploration of the trajectories of change experienced in well-being and job search self-efficacy during the career transition process. As well, relations between changes in well-being and efficacy in conducting the search for new employment and changes in the resiliency components tapped by the WRI and PsyCap were investigated. Results suggested an initial downward trajectory, followed by a subsequent upwards trajectory characterized the change in the resiliency components. This two-part trajectory was also found to characterize the pattern of change over time in the PWB and JSSE outcomes. The current study also uncovered numerous relations between change in the resiliency components and change in the PWB and JSSE outcomes, such that resiliency was often able to account for a substantial proportion of variance in the focal outcomes. Moreover, the specific relations found to be significant helped shed light on the mechanisms through which resiliency may influence PWB and JSSE during the career transition process, in theoretically plausible ways. There was also some evidence to support the incremental validity of the PsyCap. This, therefore, supported the contention that the resiliency components tapped by the WRI and PsyCap are fundamentally different, and may play a complementary role in predicting relevant outcomes after an adverse experience.
General Discussion

As I have included limitations and directions for future research in the preceding subsections, where relevant, the final section of this dissertation aims to integrate some of the findings from both Study 1 and Study 2 that are complementary in nature.

Ployhart and Vandenberg’s (2010) Requirements

Ployhart and Vandenberg (2010) noted several requirements for demonstrating evidence to support dynamic, longitudinally-oriented theories. Specifically, Ployhart and Vandenberg noted that theories involving change require that the form of change be specified (e.g., linear, nonlinear), the reasons for why the change occurs be illuminated, and the outcomes of change be discussed. As noted throughout this dissertation, both of the current studies were designed to help provide the evidence to support King and Rothstein’s (2010) model of resiliency and the WRI to satisfy Ployhart and Vandenberg’s requirements.

Study 1 revealed that change in resiliency is associated with change in one’s SDT need satisfaction. The results of Study 1 suggested that if one were to experience a substantial drop in SDT need satisfaction, as indicated by transitioning to a lower SDT need satisfaction profile over time, this would accompany a decrease in several of the resiliency variables tapped by the WRI. In contrast, no change in the level of the resiliency variables was associated with maintaining one’s Moderate or High SDT profile membership over time. Thus, a downward transition in one’s SDT profile membership was associated with a decrease in resiliency, but maintaining one SDT profile membership was related to consistency in resiliency levels over time.

Studies 1 and 2 were able to illuminate the relations between change in resiliency and changes in several outcome variables. Study 1 focused on a general measure of psychological well-being and showed that changes in resiliency were also related to changes in well-being.
In particular, larger increases in resiliency were positively related to increases in well-being. Study 2 provided further evidence to support the PWB findings from Study 1, and also provided an assessment of the relation between changes in resiliency and changes in a context-specific outcome variable, job search self-efficacy. Although the resulting relations between change in resiliency and change in JSSE were more complex than the PWB associations, they still provided evidence to support the predictive validity of changes in resiliency and the satisfaction of Ployhart and Vandenberg’s (2010) requirements.

In part, the relations uncovered between JSSE and the resiliency components were complex due to the form of resiliency over time. In particular, Study 2 offered insight into and evidence to support a non-linear trajectory of change over time in the resiliency components. Across the resiliency components tapped by the WRI, and PsyCap, there was a consistent decrease from Time 1 to Time 2, but then an increase in scores from Time 2 to Time 3. An example of this pattern was presented in Figure 6. This pattern necessitated the use of non-linear growth models, and as such, in Study 2 I examined the relations between change in resiliency and change in the PWB and JSSE outcomes from the perspective of a two-part growth model.

Therefore, changes in resiliency exhibited a two-part non-linear trajectory of change over time (at least over the study duration tapped by Study 2), were related to changes experienced in SDT need satisfaction, and were also associated with changes in the outcome variables of well-being and job search self-efficacy.

**The Why and How of Resiliency**

The current research was set out to investigate two fundamental questions over why resiliency is needed, and how it unfolds over time. Together, Studies 1 and Study 2 have provided evidence useful in providing answers to both questions. The results of Study 1
offered evidence to suggest that a substantial decrease in the satisfaction of the basic psychological needs defined by self-determination theory (Deci & Ryan, 2000) was associated with decreasing levels of resiliency. Those individuals who maintained their SDT need satisfaction were found to have also maintained their resiliency. In accordance with COR (Hobfoll, 1989), resiliency is considered an active phenomenon, and with individuals’ usage of resiliency, over time one’s levels of the resiliency components may decrease. Thus, individuals who experienced a decrease in SDT need satisfaction during the transition to university were actively using their resiliency resources to restore well-being and SDT need satisfaction. Whereas individuals who did not experience a decrease in SDT need satisfaction did not need their resiliency, and therefore maintained their scores over time.

Study 2 then offered evidence to demonstrate that resiliency unfolded with a two-part trajectory over time. In response to a challenging event, like being laid off and undergoing a career transition, over the first three months resiliency levels decreased, again demonstrating their usage by individuals coping with adversity. Subsequently, over the next three-month period, the pattern of change in the resiliency components reversed, and resiliency levels were found to generally increase. Thus, together the evidence offered by the current research has the ability to inform the literature on why resiliency is necessary and how it changes over time.

**Theoretical Contribution**

The current studies examined the role of resiliency during, and in response to, challenging life experiences and transitions. The relation between the resiliency components and individuals’ career transitions and students’ transitions to university was investigated to better understand the personal factors and processes that influence individuals’ responses to the adversities often encountered when undergoing a substantial life transition. Results
demonstrated, broadly speaking, the importance of resiliency in predicting well-being and successfully navigating the challenges of a significant transition.

Resiliency represents a unique set of constructs related to individual well-being, and the current studies highlight its functions as important determinants of recovery from adverse events. At a general level, these studies provide continued support for the importance of resiliency-related attributes and processes for individuals coping with adverse situations and events. As such, I am able to offer a unique and important contribution to the literature on individuals’ job loss experiences and also the emerging adulthood literature (e.g., Arnett, 2004) on transitioning to a university environment. In particular, these studies help provide the initial evidence of the importance of resiliency-related attributes and processes to individuals coping with job loss, and those transitioning into a university environment from high school. Thus, these studies provide compelling support for the continued study of resiliency in student populations, and organizational situations. With continued study, the empirical body of knowledge may then be leveraged to offer tailored interventions or training strategies for individuals to provide the knowledge and skills necessary to buffer against, and more adequately recover from, the stresses associated with the career transition process and other challenging life transitions.

Across many disciplines of research, the study of resiliency has previously been impeded by the lack of sound theoretical frameworks (see Luthar et al., 2000; Richardson, 2002). One of the improvements of King and Rothstein’s (2010) model of the resiliency components over other models of resiliency is the conceptualization of a multidimensional, dynamic process. King and Rothstein’s model encompasses the constant interplay of environmental and personal characteristics that over time influence the adaptive processes individuals engage in. Depending on the interaction among factors and the context within
which the process occurs, resilient outcomes can be achieved. These studies also contribute to the literature by building the body of evidence to support the model of resiliency developed by King and Rothstein (2010). By providing a comprehensive and functional model of resiliency, King and Rothstein provided an important means by which past and future knowledge of the processes and attributes related to resiliency can be better integrated and understood by researchers and practitioners. By extending the evidence available to support the propositions of King and Rothstein, further knowledge is available to support the model’s construct validity, generalizability, and usefulness. Furthermore, measurement issues impeded many previous studies investigating resiliency (see McLarnon & Rothstein, 2013), thus this study also contributes to the literature by providing additional evidence of the reliability and validity of the WRI, and supports its continued use in assessing the resiliency-related attributes of individuals coping with adverse events and situations.

The theoretical contribution of this dissertation’s studies was also represented by the fact that the WRI facets were able to explain more variation in the focal outcome variables than the competing PsyCap model. From the hierarchical logistic regression completed in Study 1 and the hierarchical multiple regression completed in Study 2, the WRI variables accounted for a substantially larger proportion of variance in Mover-Stayer status, and psychological well-being and job search self-efficacy, respectively. The WRI’s ability to demonstrate considerable predictive validity in comparison to PsyCap speaks to the advantages of using a more comprehensive model of resiliency in the prediction and explanation of positive outcomes following challenging experiences. Future researchers and practitioners would be well-advised to apply the King and Rothstein’s (2010) model and the WRI because of its more comprehensive and more theoretically-based foundations, and also the growing evidence base supporting both the theory’s and measure’s validity.
Complementary Relations with PsyCap

Throughout both studies conducted here, the results reported have seemed to suggest a complementary relation between PsyCap and the components of the resiliency tapped by the WRI. In the previous section of this Discussion I noted that the WRI and King and Rothstein (2010) model were advantageous and preferable to that of the PsyCap, however the case may be that both can play important roles in individuals’ well-being and recovery from adverse experiences. Inasmuch, PsyCap’s conceptualization of resiliency may in fact constitute a “jingle fallacy” (Block, 1995; Côté, 2014; Pedhazur & Schmelkin, 1991). The jingle fallacy is that the same label has been applied to two distinct constructs, or as Pedhazur and Schmelkin (1991) noted, it is “the belief that, because different things are called by the same name, they are the same thing” (p. 74). Thus, despite purporting to assess resiliency, PsyCap does so in name only, the construct itself, although related, may be considered conceptually distinct.

This is not to say, however, that PsyCap is necessarily inferior to the theory, measurement, and constructs associated with King and Rothstein’s (2010) model and the WRI, but simply that it is different. But this is also to say that it is different in a meaningful way that helps make the PsyCap complementary to the WRI. There are two lines of evidence to support this contention for the current set of studies. In Study 1 PsyCap demonstrated the opposite effect than that indicated by the WRI components. Specifically, for those individuals who moved, or transitioned, to a lower SDT need satisfaction profile over time, there was no change in PsyCap over time. On the other hand, for six out of the eight WRI components, those individuals in the Mover classification experienced lower scores at follow-up. Those individuals classified as SDT profile Stayers demonstrated the opposite pattern of findings for PsyCap and the WRI. For those that maintained their SDT need
satisfaction status, there was no change in the WRI components over time, but PsyCap was found to significantly increase over time. This difference, as I argued earlier, suggested that the WRI assesses resiliency components that function in relation to changes in SDT need satisfaction, whereas PsyCap taps resources that can be developed during times of SDT need satisfaction maintenance. Accordingly, the components tapped by the WRI and PsyCap play different roles in response to different experiences.

However, despite these conceptual and foundational differences between PsyCap and the resiliency components tapped by the WRI, the PsyCap can increment the prediction of important outcomes. This was shown by my earlier work in McLarnon and Rothstein (2013) and by several of the regression analyses used in Study 2. In these instances, PsyCap still contributed to the prediction and explanation of outcomes with significant regression coefficients and significant increases in squared multiple correlation estimates. PsyCap, therefore, is not necessarily inferior to the WRI, but different, and can play a complementary role in the prediction and explanation of important outcome variables.

Nevertheless, despite the positive nature of PsyCap, several of the regressions involved with Study 2 revealed negative relations with well-being and efficacy outcomes. Thus, although PsyCap may contribute to the prediction of important outcomes, it may do so in the opposite direction of relations implied by the WRI facets. Although these reversed relations do throw a wrinkle into the notion that the WRI and PsyCap are complementary, in a purely empirical sense, regardless of the direction of relations, PsyCap may still be presented as a construct worth assessing, in addition to the WRI.

This last point is especially salient if, for example, the results presented in Study 2 on the regression of Time 2 → Time 3 JSSE on the Time 2 → Time 3 predictors are considered. In the first block of the regression, which only examined the combined set of WRI variables,
SRP-B was not found to significantly add to prediction. When, however, PsyCap was added to the regression in the second step, SRP-B was found to contribute significantly. Here, PsyCap was needed for the SRP-B relation to emerge. Although it well beyond the scope of this dissertation to provide a thorough and comprehensive discussion over the aspects of multiple regression, semi-partial correlations, and the purity principle (see O’Neill et al., 2014; Spector & Brannick, 2011), to address why SRP-B was now significant, this change further suggests a complementary role. In particular, without acknowledging the role of PsyCap, the role of SRP-B wouldn’t have been considered meaningful. Together though, PsyCap and SRP-B both added to prediction, and helped account for 17% of the variance in Time 2 to Time 3 changes in JSSE.

**Longitudinal Validity**

Across different time lags and differing numbers of measurement occasions, the measurement invariance, which supports inferences of longitudinal validity, was investigated for the WRI and the PsyCap. For both measures, resounding support was found for measurement invariance over time. Specifically, across Study 1 and Study 2, the WRI and PsyCap demonstrated considerable evidence of measurement invariance, suggesting that even in consideration of possible within-person changes, the measurement invariance of both sets of constructs is upheld over time.

These demonstrations of measurement invariance, and the support they lend to propositions of longitudinal validity, represent an important facet of evidence presented by the current set of studies because they denote the consistency of the constructs over time. In particular, in consideration of Chan’s (2011) discussion of possible changes in a construct or its measure over time, supporting invariance reduces concerns over whether the measure’s properties have changed over time or whether the construct being assessed over time has
changed. Chan noted that *alpha* change represented legitimate intra-individual change given a constant conceptual domain and measurement instrument. In alpha change, observed changes could not be attributed to differences in the measurement instrument or differences in the actual construct assessed. On the other hand, *beta* or *gamma* change, represented false indications of change, in which the measurement instrument has changed over time or that meaning or conceptualization of the construct changed over time, respectively (Chan, 2011).

The demonstrations I have provided for measurement invariance and longitudinal validity underscore that beta or gamma changes are not responsible for the changes observed in either Study 1 or Study 2. Furthermore, this supported the validity of the within-person changes occurring as a result of transitioning to a university environment and occurring during the career transition process.

Together, the results of Study 1 and Study 2 provide considerable confidence in the measurement of the WRI’s resiliency components and the PsyCap over time. This supports the continued use of the WRI and PsyCap in future longitudinal studies, as researchers can be assured that the focal constructs assessed by the WRI and PsyCap are assessed with the same measurement properties over time. This thereby reduces concerns of measurement nonequivalence and the notion that the constructs have fundamentally changed over time, facilitating greater certainty in findings and accurate inferences of change over time.

**Implications**

One thing that is clear from the current research is that resiliency, and its constituent components, are important and positively related to achieving positive outcomes following challenging experiences. This has been strongly supported by previous literature (e.g., Masten, 2001; Werner & Smith, 1982), and indeed reflects common thinking about resiliency. Although the importance of resiliency is not a novel contribution of the current research, the
uniqueness of the current research offers understanding of what changes in response to a challenging event that may necessitate resiliency (i.e., substantial changes in SDT). As well, the current research offers a contribution to inform the literature on the trajectory of resiliency over time. These two predominant contributions can help offer several implications for practice.

After a challenging event has been experienced, and one’s SDT need satisfaction is substantially decreased, then one should actively make use of his or her affective, behavioral, and cognitive personal characteristics, initial response, and behavioral and cognitive self-regulatory strategies in order to restore their desired SDT levels, and thereby re-establish their psychological well-being. Although specific implications for practice aren’t available yet, as the framework for a WRI-based training and a development program have yet to be designed, the results of Study 1 do suggest where individuals and practitioners should focus their attention. In particular, as the PC-A, PC-B, PC-C, IR, SRP-B, and SRP-C facets of the WRI were found to differentiate those who moved SDT profiles and those that stayed in his or her initial SDT profile. These are the facets that can be used to inform exercises that may increase the likelihood of maintaining one’s SDT status during challenging events. Thus, by focusing on each of these resiliency components in turn, individuals and practitioners may be able to improve or maintain SDT levels and improve outcomes following challenging experiences.

To target the PC-A component, individuals could focus on tasks and activities that help build and maintain a healthy sense of esteem. Healthy is used here because optimal self-esteem has been noted to come at moderate levels, where too high or too low levels have been found to be less adaptive (Baumeister, Smart, & Boden, 1996; Guindon, 2009). Self-esteem may be bolstered by eating healthier, being proactive and not procrastinating, giving
one’s self small rewards, or by doing something nice for another person. PC-B may be open to development through programs aimed at increasing one’s sense of personal control. In this case, one might try and take more responsibility for his or her own actions, treat adversity as challenges rather than serious negative events, or take an active approach to problem-solving when faced with difficulties. As for PC-C, if one were to exercise sense-making or meaning-making in response to challenges encountered, or practice mindfulness, then one would likely be able to put a new, positive perspective on adversities and difficulties faced.

A possible facet of any training program could also target individuals’ initial reactions and responses to the experience of adversity. If one were able to, in retrospect, reduce the magnitude and impact of the challenge encountered then well-being would likely be bolstered. Though in retrospect, training an individual to think more positively about a significant challenging event after it has occurred may reduce the negative impact of the adversity, thereby improving well-being. In terms of SRP-B, a training program encouraging individuals to take a long-term perspective instead of a short-term perspective may also positively influence the maintenance of SDT satisfaction and well-being. Thus, if one is encouraged to behave in ways that are in one’s long-term best interest, that is consistent with one’s values and beliefs, he or she may be more likely to respond positively after the experience of a challenging event. By controlling impulses and managing one’s behavior, goals are more likely to be achieved, and would likely assist with achieving positive outcomes after challenging events. Finally, for SRP-C exercising positive thinking and being able to “look on the bright side” of things, despite significant adversity, would be likely to help recover and maintain SDT status and well-being. As well, monitoring one’s progress towards a goal, and being able to redirect efforts towards potentially more viable solutions for goal achievement might improve cognitive self-regulatory strategies.
Together, these six potential strategies might be of use for individuals and practitioners looking to build the components of resiliency. Of note, it is unlikely to be the case that these potential lines for improving resiliency are mutually exclusive, so that an individual may be able to target multiple components for improvement at the same time.

Study 2, on the other hand, which answered questions related to the trajectory of change over time, can also inform several practical recommendations based on the within-timepoint regression results (see Tables 22-27). First, for individuals undergoing a career transition and were just fired, it is informative to recognize the substantial downward trend during the first stage of the transition process, which goes from firing to three months post-firing. Subsequently, during the second stage, between three and six months post-firing, there is a substantial upwards trajectory. This downwards and upwards path characterized a two-part trajectory, and led to several differential relations at both stages between changes in resiliency and changes in important outcomes.

In the initial stage of the career transition process, superior outcomes resulted with higher PC-B and SRP-C, and lower OSR at follow-up. In following from the recommendations suggested above, building and developing one’s behavioral personal characteristics between the time of being fired and three months later will likely lead to achieving better well-being outcomes. On the other hand, reducing one’s level of social support, and possibly focusing attention on one’s self will also add to achieving positive outcomes during the same duration after being fired.

As well, in conjunction with decreasing one’s PsyCap resources, increasing the usage of cognitive self-regulatory strategies can help build psychological well-being in this first stage of the career transition process. As the regression results revealed that SRP-C was only able to contribute at statistically significant levels once PsyCap was introduced, based on
these results, any development program targeted on SRP-C would also have to address the
dependence on PsyCap’s role. However, facilitating decreasing PsyCap levels during a
development program focused on SRP-C would unlikely add substantial material and
training time because, in line with the results of S. J. Peterson et al. (2011), individuals
experiencing challenging events, like career transitions and job loss, are using their PsyCap
resources, thereby decreasing the amount they have available. In this way, PsyCap may
decrease without explicit need to be included in a development program, facilitating the
improvement of SRP-C and the accompanying optimal change of well-being.

During the second part of the transition process, reducing one’s levels of PC-A, IR, and SRP-B will likely help achieve a desirable level of well-being. The recommendation to reduce SRP-B comes with the caveat, that reducing one’s use of behavioral self-regulatory strategies (i.e., taking a short-term perspective, rather than a long-term perspective) was found to contribute to optimal well-being so long as PsyCap was omitted from the regression equation. Thus, decreasing SRP-B may play a role so long as an individual isn’t simultaneously undertaking a PsyCap intervention (Luthans, Avey et al., 2006; Luthans, Avey, & Patera, 2008; Luthans et al., 2010; Russo & Stoykova, 2015). This is because the effects of SRP-B and PsyCap were in different directions, and increasing PsyCap levels at the second stage of the career transition process reduced the effect of decreasing SRP-B. Practitioners should be aware of these differential relations as to make the best evidence-based decisions, one needs to be aware of the duration since firing in order to best suggest which resiliency components to develop and focus on.

Having said that, as well, another differential pattern of relations was found between the well-being variable examined and the job search self-efficacy variable. In the first part of the trajectory, focusing one’s energy and time on developing behavioral personal
characteristics and building one’s personal control will likely help improve the sense of efficacy felt towards the job search during the first stage. During the second stage of the career transition, reducing one’s level of social support, as in the recommendations noted above, can help increase job search self-efficacy. Though these recommendations to reduce social support may seem counter-intuitive, the evidence presented by Study 2 suggests that benefit may be available by reducing the amount of time spent with close social relations. As well, during the second stage of the career transition, in conjunction with increasing PsyCap, increasing one’s SRP-C can help build job search self-efficacy in the later stage of one’s career transition.

Conclusions

The first objective of the current research was to explore the changes within individuals that necessitate resiliency. Study 1, took a person-centered perspective by using latent profile analysis of the three basic psychological needs defined by Self-Determination Theory (Deci & Ryan, 2000; needs of autonomy, competence, and relatedness). Moreover, Study 1, examined the incidence of change in profile membership over time occurring in response to the challenges of one’s early university studies, and the relation between change in membership and change experienced in the components of resiliency. Substantial downward changes in profile membership were related to less usage of the resiliency components over time.

The second objective of the current research was to explore how resiliency unfolded over time. Study 2, therefore, sought to investigate the nature of the trajectory of resiliency over time in a sample of individuals that were recently laid off and undergoing a career transition process. Results suggested that a two-part trajectory, characterized by an initial downward trajectory, followed by a subsequent upwards trajectory described the change
experienced in the resiliency components over time. Furthermore, Study 2 provided evidence for the ability of the resiliency components to explain and predict changes in well-being and job search self-efficacy during the career transition process. However, given the two-part trajectory, relations between the resiliency components and the outcomes varied over time. In particular, in the early stages of one’s career transition process, optimal outcomes resulted from more of the resiliency components, whereas optimal outcomes in the later stages would likely result from less usage of the resiliency components.

Together, this research offered insight into why and how resiliency functions. With the findings presented by the current research numerous implications were highlighted in terms of practical suggestions, which together, could form the basis of a resiliency development program that could be used by practitioners to positively influence the resiliency and positive outcomes of individuals who have, and will, experience challenging events. As well, the current research offered a number theoretical contributions in the form of further evidence for the reliability and validity of the King and Rothstein (2010) model of resiliency, and its associated measure, the WRI (McLarnon & Rothstein, 2013).
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Appendix A – Latent profile analysis fit indices

Several simulation studies (e.g., Henson, Reise, & Kim, 2007; Nylund, Asparouhov, & Muthén, 2007; Tofghi & Enders, 2008; Yang, 2006) have examined the effectiveness of choosing optimal LPA models on the basis of the Akaike Information Criteria (AIC; Akaike, 1973, 1983), consistent AIC (CAIC; Bozdogan, 1987), Bayesian Information Criteria (BIC; Schwarz, 1978), sample-size adjusted BIC (aBIC; Sclove, 1987), adjusted Lo-Mendell-Rubin (aLMR; Lo, Mendell, & Rubin, 2001; Vuong, 1989) likelihood ratio test, and the bootstrapped likelihood ratio test (BLRT; McLachlan, 1987; McLachlan & Peel, 2000). This body of research has demonstrated that, generally, an optimal LPA model has the lowest AIC, CAIC, BIC, and aBIC values, and has aLMR, and BLRT p-values of less than .05. Both the aLMR and BLRT provide an assessment of increment in fit between a model with k profiles compared to a model with k-1 profiles (McLachlan & Peel, 2000). The aLMR and BLRT are necessary because the traditional likelihood ratio test (LRT) used structural equation modeling (SEM) is not available in mixture models because models differing in the number of profiles are not technically nested, and violate several regularity assumptions of the LRT (McLachlan, 1987). Further, Morin and Marsh (2015) suggested using an elbow plot of information criteria values given by the AIC, CAIC, BIC, and aBIC to assist model selection.

Based on the results of Nylund et al. (2007) and the recommendations of Lubke and Muthén (2005), I placed emphasis on the empirical indicators of fit rendered by the BIC, which reflects a model deviance estimate, and the BLRT. The use of the BLRT, and a comparison of information criteria values across LPA models can allow for more objective decisions to be made on the number of classes present than cluster analysis. However, in cases of similar BIC values emerging from distinct profile solutions (as may be indicated by the elbow plot of information criteria values; Morin & Marsh, 2015), I also considered the
entropy value associated with each model (Lubke & Muthén, 2007; Nylund-Gibson, Grimm, Quirk, & Furlong, 2014). Entropy reflects the accuracy with which cases can be classified into each profile and ranges from zero to 1.00, with values of .80 and above supporting adequate classification (Lubke & Muthén, 2007; B. O. Muthén, 2004; M. Wang, 2007). Additionally, I favored solutions that did not result in any profiles that were assigned a small number of individuals (i.e., less than 5% of the sample; Marsh, Ludtke, Trautwein, & Morin, 2009). Moreover, I preferred profile models that did not result in any statistical errors (i.e., due to negative variance estimates, non-positive definite Fisher Information matrix, non-replicated loglikelihood values across multiple starting values, out-of-bounds parameter estimates), which, if encountered can suggest “improper” (Morin, Morizot, Boudrias, & Madore, 2011, p. 80) or over-parameterized solutions (i.e., extracting too many profiles; D. J. Bauer & Shanahan, 2007).
Appendix B – Pilot Study

Method

Participants

As a component of a larger online “mass testing” study, 745 undergraduate students from a large Canadian university participated in exchange for course credit. The mean age for participants was 18.22 years ($SD = 1.19$), and ranged from 16 to 29 (18 participants did not report their age). The majority of participants identified as female (485; 65.1%), and 259 identified as male (34.8%), and one participant (0.1%) declined to provide their gender. The majority of the participants also identified as white/Caucasian (417; 56.0%). Four participants (.5%) declined to provide their ethnicity, but the remainder were from a diverse array of ethnic backgrounds, including Chinese (129; 17.3%), South Asian (Indian, Pakistani; 62; 8.3%), black/African American (8; 1.1%), Filipino (9; 1.2%), Latin American (8, 1.1%), Southeast Asian (13; 1.7%), Arab (21; 2.8%), West Asian (Iranian, Lebanese; 6; .8%), Korean (22, 3.0%), and of mixed ethnic backgrounds (46; 6.2%).

Measures

Self-Determination Theory Need Satisfaction. The degree of SDT need satisfaction was assessed using Deci et al.’s (2001) Basic Need Satisfaction (BNS). The BNS consists of 21 items in total: seven assess autonomy need satisfaction, six assess competence need satisfaction, and eight assess relatedness need satisfaction. The BNS uses nine reverse-keyed items, three on each of the autonomy, competence, and relatedness subscales. Deci et al. reported Cronbach’s $\alpha$s of .73, .84, and .79 for autonomy, competence, and relatedness, respectively. An example Autonomy item is “I generally feel free to express my ideas and opinions.” An example Competence item is “People I know tell me I am good at what I do.” An example Relatedness item is “I really like the people I interact with.” All items were
rated on a seven-point Likert scale, with anchors of “Not at all true,” “Somewhat true,” and “Very true,” at the low endpoint (rated as 1), midpoint (4) and high endpoint (7), respectively.

**Well-being.** As a measure of participants’ well-being and an outcome of SDT need satisfaction, the Questionnaire for Eudaimonic Well-Being (QEWB; Waterman et al., 2010) was used. Eudaimonic well-being (EWB) is a component of psychological well-being that refers to the fulfillment of personally-relevant goals, and the extent to which an individual feels that he/she is living consistently as his/her ‘true self’ (Sheldon, 2002; Waterman, 2008). As noted by Waterman (2008) and his colleagues (2010), EWB goes beyond considering well-being as happiness, as in hedonic terms, and is still an integral component of an individual’s overall assessment of well-being.

The QEWB consists of 21 items (seven reverse-keyed) that assess a single factor of EWB. In the development of the QEWB, Waterman et al. (2010) reported Cronbach’s αs of .86 and .85 across two independent samples. Example items include “My life is centered around a set of core beliefs that give meaning to my life,” and “As yet, I’ve not figured out what to do with my life” (reverse keyed). All QEWB items were responded to on a five-point Likert scale anchored by “Strongly disagree” and “Strongly agree” at the low and high endpoints, respectively.

**Data cleaning**

As the quality of the data in large-scale, anonymous, online surveys may be suspect, careless responding items were interspersed throughout the larger questionnaire (recall that the BNS and QEWB were embedded in a larger study). Responses from individuals who are unmotivated, inattentive to questionnaire content, or provide otherwise careless responses may have a substantial negative impact on the results of subsequent analyses (Huang, Curran, Keeney, Poposki, & DeShon, 2012; Meade & Craig, 2012). Non-purposeful responding was
flagged using three items that instructed respondents to pick a particular response option (i.e., “Please answer strongly agree to this question”). Only respondents that correctly answered all three items were included in subsequent analyses.

Additionally, respondents were screened on the basis of Mahalanobis distance. Mahalanobis distance is an index of multivariate normality that follows a $\chi^2$ distribution with degrees of freedom equal to the number of variables used in the derivation of the Mahalanobis distance estimate. Meade and Craig (2012) recommended the use of Mahalanobis distance in data screening, which along with a conservative $p$-value of .001, as recommended by Kline (2011) and Tabachnick and Fidell (2007), resulted in screening out 404 participants, and a final sample size of 745, as noted above.

**Analytical Procedure**

**Confirmatory Factor Analyses.** Prior to the LPAs conducted as part of this pilot, I ran a number of confirmatory factor analyses (CFAs) to examine the construct validity of the pilot study’s SDT and QEWB variables. Kam, Morin, Meyer, and Topolnytsky (in press) and Morin and Marsh (2015) have also recommended using factor scores saved from CFA to be used as the indicator variables in subsequent LPAs. Factor scores have several desirable properties over observed mean or sum scores. First, the factor scores have been corrected for unreliability, in that measurement error has been removed from the computation of each case’s factor score. Second, the resulting factor scores are more likely to reflect a normal distribution of scores based on the usage of a normal-theory-based maximum likelihood estimator.

I examined these CFAs by applying a partially disaggregated measurement model for each construct (Bagozzi & Edwards, 1998). Partially disaggregated models require the estimation of fewer parameters (i.e., factor loadings and residual variances) than fully
disaggregated models because they use item parcels. Item parcels are two or more items that have been averaged or summed together. In comparison to analyzing item-level data, item parcels have several advantages beyond analyzing a more parsimonious model. According to Little, Rhemtulla, Gibson, and Schoemann (2013) and Williams and O’Boyle (2008), item parcels have greater reliability, higher communalities, a higher ratio of common-to-unique variance, are more likely to be normally distributed than the original items, and result in increased statistical power. In accord with Little et al.’s recommendations for item parceling, I used the balanced approach to developing item parcels: the item with the strongest corrected item-total correlation is parceled together with the item that demonstrated the lowest corrected item-total correlation, and the item with the second highest corrected item-total correlation is parceled with the item that had the second lowest, and so forth. All CFAs were conducted with Mplus 7.31 (L. K. Muthén & Muthén, 2015), and used a robust maximum likelihood estimator.

Several CFA models were considered. First, a four-factor model with correlated factors for each of the three SDT needs and one factor for EWB was hypothesized to be the optimal model. This model was compared two alternatives: a single-factor model, which specified that the parcels from all four constructs (three SDT needs and EWB) were indicators of a single latent variable, and a two-factor model, in which all of the SDT parcels were indicators of a single latent variable, and the EWB parcels were indicators of a correlated, EWB latent variable.

The CFAs I conducted used Little, Slegers, and Card’s (2006) non-arbitrary method of model identification and scaling of factor loadings, parcel means, and latent variable means. Traditionally, CFA models are identified by either fixing the factor loading of one indicator to 1.00 or by fixing the variance of the latent variable to 1.00, and additionally by
specifying the mean of the latent variable as 0.00 (and freely estimating the means or thresholds of the indicator variables). Little’s parameterization does not change the estimates of model-data fit, but allows for latent variable parameters (mean and variance) to be expressed in the metric of the measured indicators (i.e., the seven- and five-point Likert items used to assess the SDT and EWB constructs, respectively).

CFA model fit was assessed by multiple indices: the $\chi^2$ statistic, the comparative fit index (CFI), root mean square error of approximation (RMSEA), the 90% confidence interval (CI) around the RMSEA estimate, and standardized root mean square residual (SRMR). Values greater than .90 for the CFI are often considered to be of adequate model-data fit, with values greater than .95 being indicative of strong fit (Hu & Bentler, 1999; see also Goffin, 2007). Values less than .08 and .05 for the RMSEA and less than .10 and .08 for the SRMR can be taken as evidence for acceptable and good fit, respectively (Hu & Bentler, 1999; Vandenberg & Lance, 2000). As for the RMSEA 90% CI, values less than .05 for the lower bound and less than .08 for the upper bound, or containing zero in the lower bound and less than .05 for the upper bound can suggest acceptable and good model-data fit, respectively (MacCallum, Browne, & Sugawara, 1996). Ideally the $\chi^2$ value is non-significant (i.e., $p > .05$), but since it can be overly sensitive to sample size, it may not be an appropriate measure of model-data fit in large samples, and as such I place more emphasis on the CFI and RMSEA estimates (Marsh, Hau, & Grayson, 2005; Marsh, Hau, & Wen, 2004).

Comparisons between the hypothesized model and the alternatives were examined through Satorra-Bentler scaled $\chi^2$ difference test (Satorra & Bentler, 1994). The traditional LRT of $\Delta \chi^2$ test is not appropriate when robust maximum likelihood estimators are used because the resulting difference between $\chi^2$ values is not distributed as $\chi^2$ (Satorra & Bentler,
In the case of robust maximum likelihood estimators, a scaling correction must be applied to the resulting $\chi^2$ values to ensure a correct $\Delta \chi^2$ test result.

**Latent Profile Analyses.** The LPAs conducted as part of this pilot were conducted in line with the analyses I documented in McLarnon et al. (2015) and O’Neill, McLarnon, Hoffart, Woodley, and Allen (in press). These analyses also utilized Mplus 7.31 (L. K. Muthén & Muthén, 2015) and its robust maximum likelihood estimator. Following the recommendations of Pastor, Barron, Miller, and Davis (2007) and Marsh et al. (2009) I explored the optimal profile solution by first specifying a single-profile model, and then instructing Mplus to extract an additional profile in subsequent analyses. As described in Appendix A, several criteria were considered in determining the optimal profile solution. Primarily, the elbow plot of information criteria values (AIC, CAIC, BIC, and aBIC) was closely considered, along with the $p$-values rendered by the BLRT and aLMR tests.

All LPA models were run with the following technical specifications. To avoid issues associated with the models converging on local solutions, rather than optimal, global solutions (Hipp & Bauer, 2006), models were estimated with 10,000 random sets of starting values and 100 iterations for each set of random starting values, with 100 of the best starting value sets retained for a final stage of optimizations. These specifications were informed by the recommendations of Hipp and Bauer (2006) and Morin and Marsh (2015), and provide a thorough examination of each profile solution (L. K. Muthén & Muthén, 2012, p. 622).

All LPA models were specified as having freely estimated SDT means and variances across each profile and no residual correlations. This parameterization is in line with many recent applications of LPA (see Kam et al., in press; Morin, Maïano et al., 2011; Morin & Marsh, 2015; Morin, Meyer, McInerney, Marsh, & Ganotice, 2016; see also Pastor et al. [2007] for a full set of possible parameterizations). Morin, Morizot et al. (2011) recommend
freeing the variances of LPA indicators across profile groups because the assumption of
homogeneity of variances is often untenable and unrealistic in real-world situations (see also
Peugh & Fan, 2013). Without modeling this heterogeneity, spurious profiles would likely be
extracted because to achieve a comparable level of model-fit additional profiles would be
required as compared to solutions where the variances were allowed to be unique across

Following the derivation of the optimal LPA solution, the next phase of the analytical
procedure involved examining the relation between the resulting profiles and the EWB
outcome variable. Examining mean differences in EWB across the recovered profiles
functions to provide evidence for the construct validity of the profile solution (see Marsh et
al., 2009; Morin, Maïano et al., 2011; Morin, Morizot et al., 2011; Morin & Marsh, 2015; B.
O. Muthén, 2003). Equality of EWB means across profiles was assessed using Mplus’
AUXILIARY command. This procedure relies upon a Wald \( \chi^2 \) test based on pseudo-class
draws (Asparouhov & Muthén, 2014a). The AUXILIARY command is advantageous
because EWB is not directly incorporated into the LPA model, ensuring that it does not
influence the nature of the recovered profiles. This is important because the purpose of the
profiles is to describe the population heterogeneity of the SDT variables, not the combined
heterogeneity of the SDT variables and the EWB outcome variable (see Morin et al., 2016;
Nylund-Gibson et al., 2014). These outcome analyses used the BCH procedure discussed by
Bakk and Vermunt (2016; see also Bakk, Oberski, & Vermunt, 2014; and also Bolck, Croon,
& Hagenaars, 2004, after which the procedure is named) and Asparouhov and Muthén
(2014b), which provides unbiased tests of mean equality across profiles.
Results

Descriptive statistics, variable intercorrelations, and Cronbach’s α internal consistency estimates for the SDT variables and the EWB variable for the pilot study can be found in Table A1. The correlations between the three SDT variables seem to be strong (Cohen, 1988), though not unreasonably high as to suggest multicollinearity (.58, .56, and .54 between Autonomy and Competence, Autonomy and Relatedness, and Competence and Relatedness, respectively). These estimates are also in line with previous research (e.g., Verleysen, Lambrecht, & Van Acker [2015] found correlations of .60, .32, and .50 between Autonomy and Competence, Autonomy and Relatedness, and Competence and Relatedness, respectively).

Confirmatory Factor Analyses

Table A2 presents the results of the CFAs examined. The single-factor model (Model 1) fit the data extremely poorly (CFI = .00, RMSEA = .34). Model 2, a correlated two-factor model that considered a unitary SDT latent variable and an EWB latent variable, fit the data substantially better than Model 1. However, the estimates of model-data fit for Model 2 did not reach conventional cut-offs of acceptable fit according to the CFI, RMSEA or SRMR. Model 3, with four latent factors for each of the SDT needs and EWB constructs, on the other hand, provided evidence of good model fit via the CFI, RMSEA, and SRMR estimates. Moreover, Model 3 fit the data significantly better than both Models 1 and 2. This supports the hypothesized four-factor structure, and the discriminant validity of the three SDT variables and the EWB variable. Therefore, the four-factor model was retained as optimal, and from this model, factor scores were computed and used in the subsequent LPAs.
Table A1

_Pilot Study Descriptive Statistics, Correlations, and Cronbach’s α Estimates_

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Autonomy</td>
<td>.678</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2 Competence</td>
<td>.582</td>
<td>.686</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3 Relatedness</td>
<td>.559</td>
<td>.536</td>
<td>.805</td>
<td></td>
</tr>
<tr>
<td>4 EWB</td>
<td>.385</td>
<td>.516</td>
<td>.341</td>
<td>.810</td>
</tr>
<tr>
<td>Mean</td>
<td>4.762</td>
<td>4.854</td>
<td>5.568</td>
<td>3.474</td>
</tr>
<tr>
<td>SD</td>
<td>.717</td>
<td>.811</td>
<td>.765</td>
<td>.424</td>
</tr>
</tbody>
</table>

*Note. n = 745. All correlations significant at p < .01. Cronbach’s α internal consistency estimates given on diagonal in italics. EWB = eudaimonic well-being.*
Table A2

**Confirmatory Factor Analyses for SDT and EWB Measures – Pilot Study**

<table>
<thead>
<tr>
<th>Model</th>
<th>$\chi^2$</th>
<th>$\chi^2_c$</th>
<th>df</th>
<th>CFI</th>
<th>RMSEA (90% CI)</th>
<th>SRMR</th>
<th>Comparison</th>
<th>$\Delta \chi^2$</th>
<th>$\Delta \chi^2 df$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model 1</td>
<td>5,233.542*</td>
<td>1.100</td>
<td>60</td>
<td>.000</td>
<td>.340 (.332 - .348)</td>
<td>7.804</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Model 2</td>
<td>1,740.775*</td>
<td>1.111</td>
<td>57</td>
<td>.396</td>
<td>.199 (.191 - .207)</td>
<td>.299</td>
<td>2 vs. 1</td>
<td>4,323.852*</td>
<td>3</td>
</tr>
<tr>
<td>Model 3</td>
<td>183.718*</td>
<td>1.076</td>
<td>48</td>
<td>.951</td>
<td>.062 (.052 - .071)</td>
<td>.038</td>
<td>3 vs. 1</td>
<td>4,659.559*</td>
<td>12</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>3 vs. 2</td>
<td>1,340.033*</td>
<td>9</td>
</tr>
</tbody>
</table>

*Note. n = 745. $\chi^2_c$ = scaling correction factor for $\chi^2$; SDT = self-determination theory; EWB = eudaimonic well-being; CFI = comparative fit index; RMSEA = root mean square error of approximation. Model 1 = two-factor model with all SDT parcels loading on a single latent variable, and all the EWB parcels loading on a single, correlated latent variable; Model 2 = single-factor model, with all parcels loading on one latent variable; Model 3 = hypothesized four-factor model. Values in parentheses RMSEA column represent the 90% confidence interval (CI). The $\Delta \chi^2$ column provides the Satorra-Bentler nested model comparison as denoted in the Comparison column. * $p < .001.$
Latent Profile Analyses

All LPA models converged on a well-replicated solution (i.e., the 100 best loglikelihood values from the initial stage of starting values were highly replicated), in that a true global minimum of the loglikelihood function was found for each profile solution (Morin et al., 2015). Table A3 provides the fit indices (i.e., AIC, CAIC, BIC, aBIC, aLMR, and BLRT) of each LPA model. Each model resulted in admissible parameter estimates, as Mplus did not issue any warnings about non-positive Fisher Information matrices, suggesting that each profile model is statistically appropriate.

As can be seen in Table A3, entropy values were consistently high across all five of the LPA models, suggesting that individuals could be accurately and reliably classified into each of the profiles. As well, each profile accounted for a reasonably large proportion of the total sample (see Table A4). The profile with the smallest membership was extracted by the five-profile solution, but it still had greater than 5% of the sample assigned ($n = 61, 8.2\%$). Together, based on entropy and membership proportions, each of the profile solutions emerging from the pilot test were viable solutions, in that no profiles had less than 5% of the total cases, and that each model resulted in strong estimates of entropy (i.e., greater than .83).

Across all of the LPA models with one to five profiles extracted the information criteria values continually decreased. Morin and Marsh (2015) suggest this is a common occurrence in large samples, and therefore suggested considering the elbow plot of the information criteria values, rather than strictly examining where any particular information criterion is at an absolute minimum. In other words, strict reliance on the minimum information criteria cut-off may result in over extracting profiles that may only reflect trivial improvements in model-data fit.
Table A3

Pilot Study Latent Profile Analyses Results

<table>
<thead>
<tr>
<th># Profiles</th>
<th>LL</th>
<th>LLc</th>
<th>#fp</th>
<th>AIC</th>
<th>CAIC</th>
<th>BIC</th>
<th>aBIC</th>
<th>Entropy</th>
<th>aLMR</th>
<th>BLRT</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-2033.920</td>
<td>.905</td>
<td>6</td>
<td>4079.840</td>
<td>4091.073</td>
<td>4107.520</td>
<td>4088.468</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>2</td>
<td>-1475.320</td>
<td>1.120</td>
<td>13</td>
<td>2976.640</td>
<td>3000.978</td>
<td>3036.614</td>
<td>2995.334</td>
<td>.837</td>
<td>.000</td>
<td>.000</td>
</tr>
<tr>
<td>3</td>
<td>-1177.108</td>
<td>1.281</td>
<td>20</td>
<td>2394.216</td>
<td>2431.659</td>
<td>2486.484</td>
<td>2422.976</td>
<td>.860</td>
<td>.004</td>
<td>.000</td>
</tr>
<tr>
<td>4</td>
<td>-1009.257</td>
<td>1.211</td>
<td>27</td>
<td>2072.513</td>
<td>2123.062</td>
<td>2197.075</td>
<td>2111.340</td>
<td>.871</td>
<td>.018</td>
<td>.000</td>
</tr>
</tbody>
</table>

Note. LL = model loglikelihood; LLc = scaling correction factor for loglikelihood; #fp = number of parameters estimated in each model; AIC = Akaike Information Criterion; CAIC = Consistent AIC; BIC = Bayesian Information Criterion; aBIC = sample-size adjusted BIC; Entropy = index of classification quality; aLMR = adjusted Lo-Mendell-Rubin test p-value; BLRT = bootstrapped likelihood ratio test p-value.
Table A4

**Membership Proportions for the Pilot Test Latent Profile Analyses**

<table>
<thead>
<tr>
<th>Profile</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-Profile</td>
<td>100%</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2-Profile</td>
<td>47.25%</td>
<td>52.75%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3-Profile</td>
<td>42.42%</td>
<td>25.77%</td>
<td>31.81%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4-Profile</td>
<td>19.33%</td>
<td>34.09%</td>
<td>14.63%</td>
<td>31.95%</td>
<td></td>
</tr>
<tr>
<td>5-Profile</td>
<td>8.19%</td>
<td>27.00%</td>
<td>28.59%</td>
<td>19.73%</td>
<td>16.51%</td>
</tr>
</tbody>
</table>

*Note. n = 745. Table denotes proportion of cases assigned to each profile in each of the profile models.*
Likewise, Morin and Marsh (2015) have also suggested that the BLRT results can be sensitive to sample size, and may be too liberal when indicating the number of profiles to extract when sample size is relatively large. In the current study, the BLRT results suggest that each additional profile (two through five) represent significant improvements in fit. As such, these results suggest that the two-profile model is superior to the one-profile model, and the three-profile model is superior to the two-profile model, and so on (all ps < .0004). Similarly, the aLMR may also be too liberal (Morin, Morizot et al., 2011). Here, the aLMR test suggested that the two-profile solution was superior to the one-profile model, that the three-profile model represented a significant improvement in fit over the two-profile solution, and that the four-profile model might fit the data better than the three-profile model. However, in light of the multiple statistical tests involved in the aLMR comparisons up to this point, a Bonferroni correction applied to the aLMR p-values suggests that the improvement in fit offered by the four-profile model over the three-profile model is negligible. (Instead of the traditional p < .05 omnibus cutoff, the p-value can be divided by the number of aLMR tests to maintain an overall, experiment-wise p < .05; i.e., .05/4 = .0125.) This would suggest, albeit with somewhat tentative evidence, that a three-profile solution might be optimal. Given the ambiguity of these results from the values of the information criteria (in that they did not demonstrate a minimum value across any of the profile models considered), and the results of the BLRT and aLMR, I further considered the elbow plot of the information criteria values to assist with interpreting these model fit indices and determining the number of profiles.

Figure A1 presents the elbow plot associated with the LPA results for the pilot data. As noted, across all four of the information criteria, values continue to decrease through the five-profile model. The break, however, in the elbow plot appears to occur between the three- and
Figure A1. Elbow plot of Study 1, Time 1 LPA information criteria values. AIC = Akaike information criteria; CAIC = consistent AIC; BIC = Bayesian information criteria; aBIC = sample-size adjusted BIC.
four-profile models. This break is reflected in that the information criteria values plateau with the four- (and five-) profile models. This suggests that the improvement in fit (decrease in information criteria values) is less substantial in moving from the three-profile model to the four-profile model, than compared to the improvement in fit offered by the three-profile model over the two-profile model (or the two-profile model over the single-profile model). With such a modest decrease in fit offered by the four-profile model over and above the three-profile model, I interpreted this as the four-profile model representing a trivial improvement in fit beyond the three-profile model.

Therefore, in light of the somewhat ambiguous results on which to base the model selection decision on the number of latent profiles present, I believe there is sufficient evidence to support endorsing the three-profile model as the optimal and most parsimonious solution. The information criteria and the aLMR and BLRT results suggested that the three-profile solution represented a meaningful improvement over models that extracted fewer profiles. However, according to the Bonferroni-corrected aLMR test, and the elbow plot of information criteria values, the improvement in model fit offered by the four- or five-profile models was trivial. Thus, the three-profile model was retained for further analysis.

Of note, I also examined whether the assumption of homogeneity was supportable in the current application of LPA. Table A5 provides the results of the LRTs comparing profile models with one to five profiles extracted with homogeneous and heterogeneous variance structures. Note that the traditional LRT is allowable here because each comparison is within profile models that have the same number of profiles, whereas the LMR and aBLRT are required for models that differ by \( k-1 \) profiles. Homogeneous and heterogeneous variance specifications are identical for one-profile solutions, but for the two- and greater-profile models, allowing for the variances
Table A5

**Likelihood Ratio Test Results for Unequal Variances Across Profiles**

<table>
<thead>
<tr>
<th># Profiles</th>
<th>Heterogeneous</th>
<th>Homogeneous</th>
<th>LRT</th>
<th>df</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>LL</td>
<td>LLc</td>
<td>#fp</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>-2033.92</td>
<td>.905</td>
<td>6</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>-1475.32</td>
<td>1.120</td>
<td>13</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>-1177.108</td>
<td>1.281</td>
<td>20</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>-1009.257</td>
<td>1.211</td>
<td>27</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>-927.282</td>
<td>1.714</td>
<td>34</td>
<td></td>
</tr>
</tbody>
</table>

*Note. LL = model loglikelihood; LLc = scaling correction factor for loglikelihood; #fp = number of parameters estimated in each model; LRT = likelihood ratio test statistic, computed using LLc and Satorra-Bentler (Satorra & Bentler, 2001) correction; df = degrees of freedom for each LRT. * LRT is not available for the one-profile models, because whether or not variances are specified as equal or unequal across classes has no consequence because only a single class is extracted, and in this case, regardless of specifications, the model converges on the same loglikelihood estimates. * p < .05, ** p < .01*
of the SDT indicators to vary across profiles allowed for a significant improvement in fit as compared to models with similar number of profiles that constrained the variances to equality across each profile extracted. As such, this specification will be used in all further LPAs.

After deriving an optimal LPA model, the next stage in LPA-based research is an interpretation of the profiles that were extracted by the optimal solution. In other words, the next step is to gain insight into the nature of the profile solution. This can be accomplished in two additional steps. First, the actual profiles are examined to see whether any of the profile groups have any distinct patterns of means to help differentiate the recovered groups. Second, predictor or outcome variables can be modeled (through Mplus’ AUXILIARY procedures) to examine the relations between the profile groups and any theoretically important variables.

Figure A2 presents the mean levels of the three SDT variables across the optimal three-profile solution, and is noteworthy in several regards. First off, the three profiles differ primarily on the basis of level. One group has relatively low autonomy, competence, and relatedness need satisfaction, whereas the second group appears to have moderate SDT need satisfaction levels, and the final group has comparatively higher scores on all three SDT need satisfaction variables. As such, the recovered profiles differ, not in shape, but simply in amount of SDT need satisfaction. If the profiles did differ in shape, profiles with varying ‘peaks and valleys’ of autonomy, competence, and relatedness need satisfaction would have been recovered (e.g., a profile with a dominant score for autonomy with comparatively lower scores for competence and relatedness, versus a profile with a dominant score for relatedness and low scores on autonomy and competence). Table A6 presents the mean values of the SDT variables across the three profiles depicted in Figure A2. Assessed through the multivariate delta method (Raykov & Marcoulides, 2004; as operationalized through Mplus’ MODEL CONSTRAINT command), all
Figure A2. Profile of SDT means in three-profile solution from the pilot study.
Table A6

Mean SDT Values for the Pilot Study’s Three-Profile Solution

<table>
<thead>
<tr>
<th>Profile</th>
<th>Autonomy</th>
<th>Competence</th>
<th>Relatedness</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>4.147</td>
<td>4.178</td>
<td>4.900</td>
</tr>
<tr>
<td>Moderate</td>
<td>4.818</td>
<td>4.902</td>
<td>5.671</td>
</tr>
<tr>
<td>High</td>
<td>5.438</td>
<td>5.553</td>
<td>6.314</td>
</tr>
</tbody>
</table>

*Note.* All autonomy, competence, and relatedness means differ significantly across the three profiles at $p < .001$. 
autonomy, competence, and relatedness means differed significantly across all three profiles ($ps < .001$). For example, autonomy was significantly lower in low profile group as compared to both the moderate group and the high group. As such, the profile with low scores on all three need satisfaction variables was labeled Low. Likewise, the profile groups with moderate and high scores were labeled Moderate and High, respectively.

The second component to interpreting the nature of the recovered profile solution is to examine predictors and/or outcomes of membership in each of the profiles. Of central interest at this juncture is whether the profiles differ significantly in well-being. Recall that SDT was presented as a proximal cause of well-being. Thus, EWB was treated as an outcome of SDT profile membership, such that membership in the different profile groups resulted in differences in well-being. Mean differences in the EWB variable across the SDT profiles also helps to provide evidence for the construct validity of the recovered profile solution. Table A7 provides evidence of significantly different EWB across all three SDT profiles. Thus, the High profile does indeed have significantly greater well-being than the Moderate and Low profile groups, and that the Moderate group has higher well-being than the Low group. Therefore, Hypothesis 1.1 received preliminary support, but will still be further examined in Study 1.

**Discussion**

Although this was only a pilot study used to set a benchmark for the number and nature of the profiles likely to be recovered in Study 1, several findings are worth discussing in greater detail. First, CFAs supported the independence of the three SDT need satisfaction variables. A single factor model fitting the data significantly worse than a model that specified correlated factors reflected the independence of the three SDT need satisfaction variables. If a single-factor model were to have emerged as superior, or at least equivalent, to the alternative four-factor
Table A7

<table>
<thead>
<tr>
<th></th>
<th>Low</th>
<th>Moderate</th>
<th>High</th>
<th>Overall $\chi^2(2)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>EWB</td>
<td>3.254ₐ</td>
<td>3.46₁ₐ</td>
<td>3.76₂ₐ</td>
<td>164.69₃*</td>
</tr>
</tbody>
</table>

*Notes.* Different subscripts differ at $p < .001$. EWB = eudaimonic well-being. Overall $\chi^2$ = global $\chi^2$ test, with $df = 2$, for the equality of means across all three profile groups. * $p < .001$. 
model, then the covariance between the SDT factors might have been attributable to common method variance. Thus, with the CFA results being able to strongly support a four-factor model over a single-factor model, concerns over common method bias may be minimized (see Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). Additionally, the four-factor model demonstrated strong evidence of fit with a CFI greater than .95, a RMSEA less than .08, and SRMR less than .05.

Turning to the results of the LPAs, I deemed a three-profile model as optimal. This solution presented three distinct profiles of individuals differentiated on the basis of their autonomy, competence, and relatedness need satisfaction. The decision to retain three profiles may be seen as contentious as there are no set ‘golden rules’ guiding profile enumeration decisions. As I noted above, the best practice recommendations in determining the optimal number of profiles can, in part, be informed by the information criteria values reaching a minimum (or a point at which the decrease is trivial across more complex models with additional profiles), and the aLMR and BLRT p-values. I decided to retain the three-profile model on the basis of the information criteria values reaching a plateau (see Figure A1), and the aLMR reaching a non-significant value when adjusted for multiple statistical tests. This decision, and these findings, should be considered in light that LPA is regarded as an exploratory procedure, and I have aimed to use this pilot study as a preliminary investigation into the number and nature of profiles that underlie SDT need satisfaction. Study 1 seeks to cross-validate the number and nature of the profiles recovered.

The three-profile solution I recovered was predominantly differentiated on the basis of level, such that one profile had low levels of autonomy, competence, and relatedness, one profile had moderate levels of the SDT variables, and the final profile had respectively higher SDT need
satisfaction. As such, I labeled the profiles Low, Moderate, and High. As I reviewed above, several studies have applied other person-centered analyses (albeit cluster analysis, not LPA) to the SDT. To this end, Ratelle, Guay, Vallerand, Larose, and Senécal’s (2007) study is worthy of further discussion. Ratelle et al. also noted that a three-profile model was optimal, and found that the profiles were predominantly differentiated on the basis of level. However, Ratelle et al. used the motivation variables specified by SDT (i.e., extrinsic, introjected, intrinsic, etc.; Deci & Ryan, 2000) rather than measures of the basic psychological needs, which may be considered proximal causes of well-being. Despite this difference, the results of this pilot study and the results of Ratelle et al. appear to correspond reasonably well in terms of the number and nature of the profiles recovered. Thus, whether the basic psychological needs or motivation-related SDT variables are analyzed, the optimal solution may consist of three profiles differentiated on the basis of level.

As greater satisfaction of the three SDT needs is linked to greater well-being, it was necessary to then assess the relative levels of well-being across the Low, Moderate, and High profiles. This, according to Morin, Maïano et al. (2011) corresponds to providing evidence of construct validity of the profile solution. As I presented in Table A6, there were moderate to large (e.g., Cohen, 1988) mean differences of EWB across the three profiles. Thus, the recovered profiles represent substantially meaningful differentiations on individuals’ well-being, and provide evidence to support the construct validity of the three-profile solution.

These LPAs revealed profiles that vary by level, rather than shape. Although Morin and Marsh (2015) have suggested that profile solutions that reflect shape differences are most meaningful, LPAs recovering level-only differences are still theoretically meaningful, interpretable, and valuable. This is because the profiles still reflect important differentiations in
terms of the underlying populations. Recall that mixture modeling aims to recover membership in subpopulations within a sample of data. As such, these LPA results have shed light on the presence of conceptually and qualitatively distinct populations of individuals that differ on the basis of how highly the three SDT needs are satisfied. In other words, the experience of membership in the Low profile would be qualitatively distinct from what one might experience as a member of the Moderate profile. This, in part, was highlighted by the substantial mean differences in EWB across the three profiles.

In general terms, these results provide a foundation of evidence supporting a person-centered understanding of the basic psychological needs defined by SDT. Whereas the previous examples (i.e., in de Wal, den Brok, Hooijer, Martens, & van den Beemt, 2014; Moran, Diefendorff, Kim, & Liu, 2012; Ratelle et al. 2007) of applying person-centered approaches to SDT were focused on the motivation-based constructs, this study focused on the degree of need satisfaction each individual perceived. Rather than considering the SDT basic psychological needs from a variable-centered approach (e.g., Chemolli & Gagné, 2014; Church et al., 2012; Verleysen et al., 2015), future researchers may wish to consider a person-centered approach, in which all three of the SDT variables can be considered simultaneously. Such a framework would allow for the investigation of new research questions that may reflect the combined experience or mindset of varying (High, Moderate, or Low) SDT need satisfaction fulfillment.

However, what remains to be seen is whether the three-profile solution is optimal and replicable in a different sample. Further, and getting to the heart of Study 1, are the research questions around what is the incidence of change in profile membership over time in response to a challenging experience? I have anticipated that the satisfaction of some individuals’ basic psychological needs will decrease during the transition to a university environment, and in this
regard, Study 1 aims to extend a replication of the SDT profiles across two time points to examine what resiliency variables characterize those individuals that change their status (i.e., transition from the Moderate profile at Time 1 to the Low profile at Time 2) and those individuals that maintain their status (i.e., a member of the High profile at both Time 1 and Time 2).
Appendix C – Study 1 Ethics Approval

Western Research

Principal Investigator: Dr. Michal Rothstein
Department & Institution: Social Science/Management & Organizational Studies, Western University

NMREB File Number: 16S000
Study Title: Navigating the Transition to University
Sponsor:

NMREB Initial Approval Date: September 05, 2014
NMREB Expiry Date: July 31, 2016

Documents Approved and/or Received for Information:

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<th>Document Name</th>
<th>Comments</th>
<th>Version Date</th>
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<tr>
<td>Other</td>
<td>Appendix M - Debriefing form, Time 2</td>
<td>2014/07/21</td>
</tr>
<tr>
<td>Instruments</td>
<td>Appendix L - Priming scenario for McCallum &amp; Rothstein (2013) resiliency measure (see Appendix H), Time 2</td>
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<td>Appendix J - Invitation to Time 2 survey</td>
<td>2014/07/21</td>
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<tr>
<td>Instruments</td>
<td>Appendix I - Debriefing form, Time 1</td>
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<td>Instruments</td>
<td>Appendix H - Resiliency questionnaire</td>
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</tr>
<tr>
<td>Instruments</td>
<td>Appendix G - Priming scenario for McCallum &amp; Rothstein (2013) resiliency measure (see Appendix H), Time 1</td>
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<td>Instruments</td>
<td>Appendix F - Psychological well-being questionnaire</td>
<td>2014/07/21</td>
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<td>Instruments</td>
<td>Appendix E - Resiliency questionnaire</td>
<td>2014/07/21</td>
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<td>Instruments</td>
<td>Appendix D - Self-Determination Theory questionnaires</td>
<td>2014/07/21</td>
</tr>
<tr>
<td>Other</td>
<td>Appendix A - Study details to be presented on SIGNA</td>
<td>2014/07/21</td>
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<td>Western ROMEO protocol form, Version 2 (08/17/2014), clean copy</td>
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<td>Instruments</td>
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</tbody>
</table>

The Western University Non-Medical Research Ethics Board (NMREB) has reviewed and approved the above named study, as of the HSREB Initial Approval Date noted above.

NMREB approval for this study remains valid until the NMREB Expiry Date noted above, conditional to timely submission and acceptance of HSREB Continuing Ethics Review.

The Western University NMREB operates in compliance with the Tri-Council Policy Statement: Ethical Conduct for Research Involving Humans (TCPS2), the Ontario Personal Health Information Protection Act (PHIPA, 2004), and the applicable laws and regulations of Ontario.

Members of the NMREB who are named as Investigators in research studies do not participate in discussions related to, nor vote on such studies when they are presented to the IRB.

The NMREB is registered with the U.S. Department of Health & Human Services under the IRB registration number 00000941.

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Miss Methuali mmethuali@uwo.ca
Vikki Tran vitr101@uwo.ca

This is an official document. Please retain the original in your files.
Appendix D – Self-Determination Theory Questionnaire

<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
</tr>
</thead>
<tbody>
<tr>
<td>Strongly Disagree</td>
<td>Disagree</td>
<td>Neither Disagree nor Agree</td>
<td>Agree</td>
<td>Strongly Agree</td>
</tr>
<tr>
<td>1. I feel like I can be myself.</td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>D</td>
</tr>
<tr>
<td>2. I often feel like I have to follow other people’s commands.</td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>D</td>
</tr>
<tr>
<td>3. If I could choose, I would do things differently.</td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>D</td>
</tr>
<tr>
<td>4. The tasks I have to do are in line with what I really want to do.</td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>D</td>
</tr>
<tr>
<td>5. I feel free to do things the way I think they could best be done.</td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>D</td>
</tr>
<tr>
<td>6. I feel forced to do things I do not want to do.</td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>D</td>
</tr>
<tr>
<td>7. I master the tasks I have to do.</td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>D</td>
</tr>
<tr>
<td>8. I feel competent.</td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>D</td>
</tr>
<tr>
<td>9. I doubt whether I will be able to finish tasks successfully.</td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>D</td>
</tr>
<tr>
<td>10. I am good at the things I do in my job.</td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>D</td>
</tr>
<tr>
<td>11. I have the feeling that I can even accomplish the most difficult tasks.</td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>D</td>
</tr>
<tr>
<td>12. I don’t really feel connected with other people at university.</td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>D</td>
</tr>
<tr>
<td>13. At university, I feel part of a group.</td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>D</td>
</tr>
<tr>
<td>14. I don’t really mix with other people at university.</td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>D</td>
</tr>
<tr>
<td>15. I can talk with people about things that really matter to me.</td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>D</td>
</tr>
<tr>
<td>16. I often feel alone when I am with other students.</td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>D</td>
</tr>
<tr>
<td>17. Some people I go to class with are close friends of mine.</td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>D</td>
</tr>
<tr>
<td>18. I feel like I am free to decide for myself how to live my life.</td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>D</td>
</tr>
</tbody>
</table>
## Appendix E – Psychological Well-Being Questionnaire

<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
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<th>D</th>
<th>E</th>
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</thead>
<tbody>
<tr>
<td>Strongly Disagree</td>
<td>Disagree</td>
<td>Neither Disagree nor Agree</td>
<td>Agree</td>
<td>Strongly Agree</td>
</tr>
</tbody>
</table>

1. I have confidence in my opinions even if they are contrary to the general consensus.  
2. I tend to be influenced by people with strong opinions.  
3. I judge myself by what I think is important, not by what others think is important.  
4. I am good at managing the responsibilities of daily life.  
5. In general, I feel I am in charge of the situation in which I live.  
6. The demands of everyday life don't often get me down.  
7. I think it is important to have new experiences that challenge how you think about yourself and the world.  
8. For me, life has been a continuous process of learning, changing, and growth.  
9. I never wanted to give up trying to make improvements or changes in my life.  
10. People would describe me as a giving person, willing to share my time with others.  
11. Maintaining close relationships has been easy for me.  
12. I have experienced many warm and trusting relationships with others.  
13. I sometimes feel as if I have done all there is to do in life.  
14. Some people wander aimlessly through life, but I am not one of them.  
15. I live life one day at a time, and don’t really think about the future.  
16. I feel as if I have accomplished many admirable achievements in life.  
17. When I look at the story of my life, I am pleased about how things have turned out.  
18. I like most parts of my personality.
Appendix F – Psychological Capital (PsyCap) Questionnaire – Selected Items

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
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<tbody>
<tr>
<td></td>
<td>Strongly Disagree</td>
<td>Disagree</td>
<td>Neither Disagree nor Agree</td>
<td>Agree</td>
<td>Strongly Agree</td>
</tr>
<tr>
<td>13.</td>
<td>When I have a setback, I have trouble recovering from it, and moving on.</td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>D</td>
</tr>
<tr>
<td>14.</td>
<td>I usually manage difficulties one way or another.</td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>D</td>
</tr>
<tr>
<td>15.</td>
<td>I can be “on my own,” so to speak, if I have to.</td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>D</td>
</tr>
<tr>
<td>16.</td>
<td>I usually take stressful things in stride.</td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>D</td>
</tr>
<tr>
<td>17.</td>
<td>I can get through difficult times because I've experienced difficulty before.</td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>D</td>
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</tbody>
</table>
## Appendix G – Workplace Resiliency Inventory Questionnaire

<table>
<thead>
<tr>
<th></th>
<th>A Strongly Disagree</th>
<th>B Disagree</th>
<th>C Neither Disagree nor Agree</th>
<th>D Agree</th>
<th>E Strongly Agree</th>
</tr>
</thead>
<tbody>
<tr>
<td>PC-A</td>
<td>1. I can control my emotions.</td>
<td>A B C D E</td>
<td></td>
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<tr>
<td></td>
<td>2. I am not easily bothered.</td>
<td>A B C D E</td>
<td></td>
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<tr>
<td></td>
<td>3. I am not easily irritated.</td>
<td>A B C D E</td>
<td></td>
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<td></td>
<td>4. I rarely get mad.</td>
<td>A B C D E</td>
<td></td>
<td></td>
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<td></td>
<td>5. I get stressed out easily.</td>
<td>A B C D E</td>
<td></td>
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<td></td>
<td>6. I get upset easily.</td>
<td>A B C D E</td>
<td></td>
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<td></td>
<td>7. My mood changes frequently.</td>
<td>A B C D E</td>
<td></td>
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<td></td>
<td>8. I am often overwhelmed by my emotions.</td>
<td>A B C D E</td>
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<td></td>
<td>9. I get easily caught up with my emotions.</td>
<td>A B C D E</td>
<td></td>
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<tr>
<td>PC-B</td>
<td>10. I push myself very hard to succeed.</td>
<td>A B C D E</td>
<td></td>
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<tr>
<td></td>
<td>11. I am exacting in my work.</td>
<td>A B C D E</td>
<td></td>
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<td></td>
<td>12. I complete tasks successfully.</td>
<td>A B C D E</td>
<td></td>
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<tr>
<td></td>
<td>13. I stop working when it becomes too difficult.</td>
<td>A B C D E</td>
<td></td>
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<tr>
<td></td>
<td>15. I am a goal-oriented person.</td>
<td>A B C D E</td>
<td></td>
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<tr>
<td></td>
<td>16. I maintain my focus on completing tasks.</td>
<td>A B C D E</td>
<td></td>
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<tr>
<td></td>
<td>17. I don't complete tasks that I start.</td>
<td>A B C D E</td>
<td></td>
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<td></td>
<td>18. I know how to get things done.</td>
<td>A B C D E</td>
<td></td>
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<tr>
<td>PC-C</td>
<td>19. I enjoy reading challenging material.</td>
<td>A B C D E</td>
<td></td>
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<td></td>
<td>20. I find political discussions interesting.</td>
<td>A B C D E</td>
<td></td>
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<tr>
<td></td>
<td>21. I am interested in a broad range of things.</td>
<td>A B C D E</td>
<td></td>
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<tr>
<td></td>
<td>22. I avoid difficult reading material.</td>
<td>A B C D E</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>23. I am not interested in abstract ideas.</td>
<td>A B C D E</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>24. I try to avoid complex people and issues.</td>
<td>A B C D E</td>
<td></td>
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<td></td>
<td>25. I try to avoid philosophical discussions.</td>
<td>A B C D E</td>
<td></td>
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<tr>
<td></td>
<td>26. I am not interested in discussing theoretical issues.</td>
<td>A B C D E</td>
<td></td>
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<tr>
<td>IR</td>
<td>27. Following the event I was afraid that I would not be able to cope with the change.</td>
<td>A B C D E</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>28. Following the event I was more anxious than usual.</td>
<td>A B C D E</td>
<td></td>
<td></td>
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</tr>
<tr>
<td></td>
<td>29. Following the event I was more stressed than usual.</td>
<td>A B C D E</td>
<td></td>
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<tr>
<td></td>
<td>30. Following the event I was unusually depressed.</td>
<td>A B C D E</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>31. Following the event I was unable to maintain a positive outlook on things.</td>
<td>A B C D E</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>32. Following the event I felt as if my world was falling apart.</td>
<td>A B C D E</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Item</td>
<td>Statement</td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>D</td>
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</tr>
<tr>
<td>33.</td>
<td>I know there is someone I can depend on when I am troubled.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>34.</td>
<td>I know there is someone that I can go to for advice.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>35.</td>
<td>I know there is someone that I can count on to be there for me.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>36.</td>
<td>I feel that there is somebody I can talk to that will listen to my problems and concerns.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>37.</td>
<td>I know that someone will make time for me if I need them.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>38.</td>
<td>Since the significant event/experience I have more often based my goals in life on feelings, rather than logic.</td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>D</td>
</tr>
<tr>
<td>39.</td>
<td>Since the significant event/experience I have preferred to plan my life based on how I feel.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>40.</td>
<td>Since the significant event/experience I have planned my life logically and rationally.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>41.</td>
<td>Since the significant event/experience important decisions I have had to make have been based on logical reasoning.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>42.</td>
<td>Since the significant event/experience I have preferred to make decisions based on facts, not feelings.</td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>43.</td>
<td>Since the significant event/experience I have rarely overindulged.</td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>D</td>
</tr>
<tr>
<td>44.</td>
<td>Since the significant event/experience I have often jumped into things without thinking through them.</td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>45.</td>
<td>Since the significant event/experience I have often like to act on a whim.</td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>46.</td>
<td>Since the significant event/experience I have often made last-minute plans.</td>
<td></td>
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</tr>
<tr>
<td>47.</td>
<td>Since the significant event/experience I have been a highly disciplined person.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>48.</td>
<td>Since the significant event/experience I have been able to refrain from doing things that may be bad for me in the long run, even if they might make me feel good in the short term.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>49.</td>
<td>Since the significant event/experience I have tended to start tasks right away.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>50.</td>
<td>Since the significant event/experience I have found myself procrastinating from work more often.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>51.</td>
<td>Since the significant event/experience I have needed more of a push to get started on a project.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>52.</td>
<td>Since the significant event/experience I have tended to be discouraged easily.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>53.</td>
<td>Since the significant event/experience I have been disappointed with my shortcomings.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>54.</td>
<td>Since the significant event/experience it has been easy for me to look on the bright side.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>55.</td>
<td>Since the significant event/experience I have had a dark outlook for the future.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>56.</td>
<td>Since the significant event/experience I have tended see potential difficulties everywhere.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>57.</td>
<td>Since the significant event/experience I have questioned my ability to do my work properly.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>58.</td>
<td>Since the significant event/experience I have been filled with doubts.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>59.</td>
<td>Since the significant event/experience I have been afraid that I will do the wrong thing.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>60.</td>
<td>Since the significant event/experience I have found it easy to control my thoughts.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* Indicates that item is reverse-scored.
Appendix H – Priming Scenario for Study 1

Please recall a challenging or adverse event that you have recently experienced during your transition to university.

In the space below, please briefly describe ‘what happened,’ and what you thought and felt about it, as if you were telling this to a close friend.

________________________________________________________

________________________________________________________

________________________________________________________

________________________________________________________

________________________________________________________
Appendix I – Latent Profile Invariance Steps

As noted, the sequence of analytical steps for testing the invariance of latent profiles is relatively new. In fact, Nylund et al. (2006) suggested that invariance is generally just assumed in LTA, and not explicitly tested. However, the analytical tools necessary for assessing the invariance of two or more LPA solutions are readily available when drawing from the methodological literature on confirmatory LCA. Essentially, the confirmatory LCA framework can be extended to accommodate confirmatory LPA. Recently, Morin, Meyer, Creusier, & Biétry (2016) highlighted the analytical steps necessary to apply confirmatory LPA and document the invariance of LPA solutions. In extending this work, I also thoroughly consulted the methodological literature on confirmatory LCA. As such, the confirmatory LPA models that follow have been informed not only by Morin et al., but also the work of Eid, Langeheine, and Diener, (2003), Finch and Bronk (2011), Geiser, Lehmann, and Eid (2006), Hoferichter, Raufelder, Eid, and Bukowski (2014), Kankaraš, Moors, and Vermunt (2011), and Kankaraš, Vermunt, and Moors (2011).

There are four analytical steps proposed here to investigate the invariance of LPA solutions. First is configural invariance, which is assessed by whether the same number of profiles is present across timepoints (or groups). This step functions as the baseline model on which additional, and more restrictive models are based. After conducting LPAs at each timepoint (or in each group) separately, if the same number of profiles is found then configural invariance is supported. Once configural invariance is supported, additional tests of invariance can be conducted. If configural invariance is not supported, subsequent tests of invariance are not recommended. This is because the nature of the profile solutions differs, leaving further comparisons ambiguous and making it difficult to accurately apply more specific equality
constraints (i.e., an equality constraint to test whether the Low profile group has similar autonomy means across timepoints). Morin et al. (2016) suggested that if configural invariance is not supported, comparisons between LPA solutions can be facilitated through a qualitative process, rather than a quantitative one, as specified here.

Next, if configural invariance has been supported, structural invariance is assessed through implementing equality constraints over the means of the indicators in each respective profile group. This step assesses whether the profiles that have emerged have the same mean structure. Morin et al. (2016) noted that if structural invariance is not supported then any additional assessment of invariance or any subsequent analyses should be conducted separately across timepoints or groups because the nature of the profiles differs and are not comparable.

The third analytical step is dispersive invariance. As dispersion might suggest, this step assesses whether the variances, or, specifically, the residual variances, of each LPA indicator are similar within each profile across timepoints (or groups). Thus, including equality constraints on the variances of each indicator across profile solutions, in addition those included for structural invariance, assesses within-profile similarity of cases assigned to each profile. If dispersive invariance is not supported it suggests that the cases are not prototypical across the LPA solutions, such that the cases assigned to each profile are more heterogeneous across solutions. Morin et al. (2016) suggested that dispersive invariance is not necessary for subsequent analyses, but can be an important step to document whether the profiles are internally consistent across LPA solutions.

The fourth stage for LPA invariance is distributional invariance. This step assesses whether the same proportions of a sample are assigned to each profile. In other words, the distributional invariance assesses whether the relative sizes of each profile are similar across
timepoints (or groups). Distributional invariance is assessed by including equality constraints on
the threshold parameters of the latent categorical variable, which reflect likely membership in
each profile. Supporting distributional invariance demonstrates that the frequency of membership
in each profile is similar across timepoints. If distributional invariance is not supported some
profiles may be more or less predominant across timepoints. As in dispersional invariance,
distributional invariance can be used to further document the replicability of a profile solution
across timepoints, but it is not a necessity for further cross-timepoint or cross-group analyses.

Morin et al. (2016) also discuss the possibility of assessing deterministic and predictive
invariance. Deterministic invariance assesses whether covariates or predictors of profile
membership function the same across timepoints or groups. Predictive invariance assesses
whether outcomes of profile membership replicate across timepoints or groups. However, for the
present study, the focus is not on predictors or outcomes of profile membership. As such, only
the configural, structural, dispersional, and distributional invariance of the Time 1 and Time 2
LPA solutions was estimated. These steps, representing a confirmatory LPA, are necessary to
ensure that the transitions between profiles over time are readily interpretable.

Drawing from the previous examples of confirmatory LCA, the steps described here (and
by Morin et al., 2015) mimic that of the unrestricted, semi-restricted, and fully-restricted models
described by Eid et al. (2003), Geiser et al. (2006), and Hoferichter et al. (2014). The unrestricted
model is one in which no equality constraints are imposed on the combined model, and that
number and nature of the profiles are free to vary across timepoints or groups. This would
represent conducting LPAs independently, before combining solutions in a single model. The
semi-restricted model reflects the combined assessment of configural and structural invariance in
that the number of profiles and response probabilities (item thresholds) are constrained to
equality across timepoints or groups. The semi-restricted model places no constraints on the proportion of cases assigned to each profile, but in the fully-restricted model, equality constraints on the membership probabilities are implemented in addition to the constraints of the semi-restricted model. Morin et al. noted that the equivalence of dispersional invariance may not be appropriate for categorical indicators in LCA, and thus this component of MI testing is omitted from the examples provided by Eid et al., Geiser et al., and Hoferichter et al.

Invariance of the LPA or LCA models can be supported through multiple methods. First off, nested model comparisons using LRTs can be conducted to assess whether the constraints of the structural, dispersional, and distributional models significantly decrease model fit (see Eid et al., 2003; Kankaraš, Moors, & Vermunt, 2011). The traditional LRTs can be used for nested model comparisons because, for example, the structural invariance model is nested within the configurally-invariant model. These models don’t differ in the number of profiles extracted, so that the regularity conditions surrounding the LRT, and its $\chi^2$ analogue, are met (see Lubke & Muthén, 2005; McLachlan, 1987; Nylund et al., 2006; see also Finch & Bronk, 2011; McCutcheon, 2002). These LRTs, can also be conducted accurately in conjunction with a robust maximum likelihood estimator, using the Satorra-Bentler correction (Satorra & Bentler, 1995; see also L. K. Muthén, 2010). However, as in previous usage, the LRT can be sensitive to sample size and may be overpowered in large samples, and as such, may signal non-invariance even if the degree of non-invariance is trivial (see also Kankaraš, Moors, & Vermunt, 2011). As such, I have supplemented these LRTs with an assessment of the change in the information criteria (i.e., AIC, CAIC, BIC, and aBIC) values across the steps of LPA MI. Of note, Hoferichter et al. (2014) placed emphasis on comparing BIC estimates to when drawing invariance conclusions (see also Eid et al., 2003, Geiser et al., 2006). One reason for this might be because the BIC
includes a punishment for model complexity (Schwarz, 1978). Thus, if the BIC decreases across invariance models it may indicate that the increase in parsimony from reducing the number of parameters is greater than the misfit caused by imposing equality constraints on parameters that differ modestly. Invariance of LPA solutions can therefore be supported when the BIC decreases across sequential analyses.
Appendix J – Study 1 Drop-out Effects

Table A8

*Logistic Regression: Stayers versus Leavers*

<table>
<thead>
<tr>
<th></th>
<th>b</th>
<th>SE</th>
<th>OR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-5.567</td>
<td>4.097</td>
<td>.003</td>
</tr>
<tr>
<td>Sex</td>
<td>.123</td>
<td>.324</td>
<td>1.131</td>
</tr>
<tr>
<td>Age</td>
<td>.285</td>
<td>.188</td>
<td>1.330</td>
</tr>
<tr>
<td>SDT-A</td>
<td>-0.032</td>
<td>.319</td>
<td>.968</td>
</tr>
<tr>
<td>SDT-C</td>
<td>.045</td>
<td>.286</td>
<td>1.046</td>
</tr>
<tr>
<td>SDT-R</td>
<td>-.009</td>
<td>.221</td>
<td>.991</td>
</tr>
<tr>
<td>PC-A</td>
<td>.126</td>
<td>.259</td>
<td>1.135</td>
</tr>
<tr>
<td>PC-B</td>
<td>.353</td>
<td>.360</td>
<td>1.423</td>
</tr>
<tr>
<td>PC-C</td>
<td>-.665*</td>
<td>.242</td>
<td>.514</td>
</tr>
<tr>
<td>OSR</td>
<td>.025</td>
<td>.190</td>
<td>1.025</td>
</tr>
<tr>
<td>IR</td>
<td>.146</td>
<td>.267</td>
<td>1.158</td>
</tr>
<tr>
<td>SRP-A</td>
<td>-.279</td>
<td>.235</td>
<td>.757</td>
</tr>
<tr>
<td>SRP-B</td>
<td>.105</td>
<td>.258</td>
<td>1.110</td>
</tr>
<tr>
<td>SRP-C</td>
<td>.425</td>
<td>.304</td>
<td>1.530</td>
</tr>
<tr>
<td>PsyCap</td>
<td>-.515</td>
<td>.536</td>
<td>.598</td>
</tr>
<tr>
<td>PWB</td>
<td>.786</td>
<td>.565</td>
<td>2.195</td>
</tr>
</tbody>
</table>

Nagelkerke $R^2$ | .090 |
Cox & Snell $R^2$ | .055 |
-2LL | 34.593 |
$\chi^2$ (df) | 21.863 (16) |

*Note. OR = odds ratios. *p < .01.*
Table A9

*T-tests: Stayers versus Leavers*

<table>
<thead>
<tr>
<th></th>
<th>Stayer</th>
<th>Leaver</th>
<th>( t(398) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sex</td>
<td>1.713 (.453)</td>
<td>1.616 (.490)</td>
<td>-1.536</td>
</tr>
<tr>
<td>Age</td>
<td>18.269 (1.167)</td>
<td>18.014 (.736)</td>
<td>-1.791</td>
</tr>
<tr>
<td>SDT-A</td>
<td>3.621 (.571)</td>
<td>3.614 (.664)</td>
<td>-0.084</td>
</tr>
<tr>
<td>SDT-C</td>
<td>3.637 (.629)</td>
<td>3.559 (.747)</td>
<td>-0.928</td>
</tr>
<tr>
<td>SDT-R</td>
<td>3.646 (.847)</td>
<td>3.612 (.778)</td>
<td>-0.317</td>
</tr>
<tr>
<td>PC-A</td>
<td>3.078 (.710)</td>
<td>3.082 (.742)</td>
<td>0.047</td>
</tr>
<tr>
<td>PC-B</td>
<td>3.938 (.512)</td>
<td>3.862 (.628)</td>
<td>-1.088</td>
</tr>
<tr>
<td>PC-C</td>
<td>3.284 (.661)</td>
<td>3.525 (.671)</td>
<td>2.757*</td>
</tr>
<tr>
<td>OSR</td>
<td>4.366 (.833)</td>
<td>4.237 (.743)</td>
<td>-1.208</td>
</tr>
<tr>
<td>IR</td>
<td>2.659 (.704)</td>
<td>2.671 (.623)</td>
<td>0.131</td>
</tr>
<tr>
<td>SRP-A</td>
<td>3.364 (.655)</td>
<td>3.429 (.699)</td>
<td>0.743</td>
</tr>
<tr>
<td>SRP-B</td>
<td>3.102 (.649)</td>
<td>2.997 (.714)</td>
<td>-1.205</td>
</tr>
<tr>
<td>SRP-C</td>
<td>3.095 (.704)</td>
<td>2.964 (.732)</td>
<td>-1.396</td>
</tr>
<tr>
<td>PsyCap</td>
<td>3.537 (.461)</td>
<td>3.512 (.549)</td>
<td>-0.391</td>
</tr>
<tr>
<td>PWB</td>
<td>3.806 (.399)</td>
<td>3.727 (.439)</td>
<td>-1.479</td>
</tr>
</tbody>
</table>

*Note.* Standard deviations in parentheses. *\( p < .05 \).*
### Differences in Variances: Whole Sample versus Stayers

<table>
<thead>
<tr>
<th>Variable</th>
<th>Whole Sample</th>
<th>Stayer</th>
<th>$z^a$</th>
</tr>
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<tbody>
<tr>
<td>Sex</td>
<td>.213</td>
<td>.205</td>
<td>-.431</td>
</tr>
<tr>
<td>Age</td>
<td>1.221</td>
<td>1.363</td>
<td>1.508</td>
</tr>
<tr>
<td>SDT-A</td>
<td>.346</td>
<td>.326</td>
<td>-.749</td>
</tr>
<tr>
<td>SDT-C</td>
<td>.425</td>
<td>.396</td>
<td>-.897</td>
</tr>
<tr>
<td>SDT-R</td>
<td>.695</td>
<td>.717</td>
<td>.406</td>
</tr>
<tr>
<td>PC-A</td>
<td>.511</td>
<td>.504</td>
<td>-.176</td>
</tr>
<tr>
<td>PC-B</td>
<td>.285</td>
<td>.262</td>
<td>-1.055</td>
</tr>
<tr>
<td>PC-C</td>
<td>.446</td>
<td>.437</td>
<td>-.280</td>
</tr>
<tr>
<td>OSR</td>
<td>.669</td>
<td>.693</td>
<td>.469</td>
</tr>
<tr>
<td>IR</td>
<td>.476</td>
<td>.496</td>
<td>.549</td>
</tr>
<tr>
<td>SRP-A</td>
<td>.439</td>
<td>.430</td>
<td>-.292</td>
</tr>
<tr>
<td>SRP-B</td>
<td>.438</td>
<td>.422</td>
<td>-.475</td>
</tr>
<tr>
<td>SRP-C</td>
<td>.504</td>
<td>.496</td>
<td>-.213</td>
</tr>
<tr>
<td>PsyCap</td>
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<td>.212</td>
<td>-.873</td>
</tr>
<tr>
<td>PWB</td>
<td>.166</td>
<td>.160</td>
<td>-.504</td>
</tr>
</tbody>
</table>

*Note.* $n_{\text{Whole Sample}} = 400$, $n_{\text{Stayer}} = 338$. $^* p < .01$. $^a$ two-tailed $z$-test as detailed in Goodman & Blum (1996), critical $z = |1.960|$. 

---

Resiliency and Well-being
Table A11

*Results of Regression Analyses: Psychological Well-Being*

<table>
<thead>
<tr>
<th></th>
<th>Whole Sample</th>
<th></th>
<th>Stayers</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>b</td>
<td>SE</td>
<td>b</td>
<td>SE</td>
<td>t</td>
</tr>
<tr>
<td>Sex</td>
<td>.010</td>
<td>.030</td>
<td>-.019</td>
<td>.032</td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>-.013</td>
<td>.012</td>
<td>-.025*</td>
<td>.012</td>
<td>.118 (p = .906)*</td>
</tr>
<tr>
<td>SDT-A</td>
<td>.088*</td>
<td>.029</td>
<td>.064*</td>
<td>.032</td>
<td></td>
</tr>
<tr>
<td>SDT-C</td>
<td>.023</td>
<td>.027</td>
<td>.015</td>
<td>.029</td>
<td></td>
</tr>
<tr>
<td>SDT-R</td>
<td>.031</td>
<td>.020</td>
<td>.022</td>
<td>.021</td>
<td></td>
</tr>
<tr>
<td>PC-A</td>
<td>-.022</td>
<td>.024</td>
<td>-.033</td>
<td>.025</td>
<td></td>
</tr>
<tr>
<td>PC-B</td>
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<td>.032</td>
<td>.129*</td>
<td>.036</td>
<td></td>
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<tr>
<td>PC-C</td>
<td>-.013</td>
<td>.021</td>
<td>-.012</td>
<td>.023</td>
<td></td>
</tr>
<tr>
<td>OSR</td>
<td>.078*</td>
<td>.018</td>
<td>.104*</td>
<td>.020</td>
<td></td>
</tr>
<tr>
<td>IR</td>
<td>-.023</td>
<td>.024</td>
<td>-.046</td>
<td>.025</td>
<td></td>
</tr>
<tr>
<td>SRP-A</td>
<td>.008</td>
<td>.022</td>
<td>.008</td>
<td>.024</td>
<td></td>
</tr>
<tr>
<td>SRP-B</td>
<td>.023</td>
<td>.024</td>
<td>.029</td>
<td>.026</td>
<td></td>
</tr>
<tr>
<td>SRP-C</td>
<td>.008</td>
<td>.028</td>
<td>.012</td>
<td>.030</td>
<td></td>
</tr>
<tr>
<td>PsyCap</td>
<td>.390*</td>
<td>.046</td>
<td>.379*</td>
<td>.049</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>1.334*</td>
<td>.299</td>
<td>1.737*</td>
<td>.311</td>
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</table>

<table>
<thead>
<tr>
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<th>Whole Sample</th>
<th></th>
<th>Stayers</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>F</td>
<td></td>
<td>R²</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>46.990</td>
<td></td>
<td>.639*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Adjusted R²</td>
<td></td>
<td>.626</td>
<td></td>
<td>.629</td>
</tr>
</tbody>
</table>

*Note.* Table presents unstandardized coefficients. \(n_{\text{Whole Sample}} = 400, n_{\text{Stayer}} = 338.* \( p < .05.* Two-tailed \(t\)-tests are shown for the difference between coefficients that were found to be significant in the Whole Sample, but not in the Stayers, and vice versa.
Appendix K – Longitudinal Measurement Invariance

**Self-determination theory.** The MI analyses for the SDT need satisfaction measure can be found in Table A8. The configural invariance model demonstrated adequate fit to the data with a CFI = .977 (correction for a longitudinally correct null model only resulted in a very modest change: \(^{12}\) CFI = .976), RMSEA = .036 (90% CI = .025 - .047). Adding the equality constraints necessary to estimate respective factor loadings as equivalent across timepoints was found to be non-significant according to the \(\Delta \chi^2\) test, \(^{13}\) and the \(\Delta\)CFI and \(\Delta\)RMSEA guidelines noted above. Thus, the factor loadings of the SDT need satisfaction measures were found to be invariant across timepoints. Adding the equality constraints on respective item parcel means across timepoints was found to significantly decrease model fit according to the \(\Delta \chi^2(6) = 32.063, p < .001\). However, the \(\Delta\)CFI and \(\Delta\)RMSEA values were below the guidelines for supporting MI (-.009 and .006, respectively), thus the SDT need satisfaction measure demonstrated strong invariance across time.

The next stage of the SDT measure’s MI analyses assessed whether the residual variances of each respective item parcel was equivalent across timepoints. As in the test of mean invariance, imposing equality constraints upon the Time 1 and Time 2 item parcel residuals resulted in a significant decrease in model fit, \(\Delta \chi^2(9) = 30.434, p < .001\). On the other hand, invariance was supported in that both the \(\Delta\)CFI and \(\Delta\)RMSEA values were below the respective cut-offs (-.009 and .004, respectively). Notably, this demonstration of strict invariance facilitates valid comparisons across timepoints.

\(^{12}\) This was the same result in the other measures assessed in Study 1 as well. Despite the trivial differences, all CFI estimates reported in Study 1 (and Study 2) have been derived from the longitudinally correct null model.

\(^{13}\) All \(\Delta \chi^2\) tests reported were also adjusted according to the Satorra and Bentler (1994) scaled difference tests for use with robust maximum likelihood estimators.
### Table A12

**Self-Determination Theory Longitudinal Measurement Invariance Analyses**

<table>
<thead>
<tr>
<th></th>
<th>$\chi^2$</th>
<th>$\chi^2_c$</th>
<th>$\chi^2 df$</th>
<th>#fp</th>
<th>CFI</th>
<th>RMSEA</th>
<th>$\Delta\chi^2$</th>
<th>$\Delta\chi^2 df$</th>
<th>$\Delta$CFI</th>
<th>$\Delta$RMSEA</th>
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</thead>
<tbody>
<tr>
<td><strong>Configural</strong></td>
<td>169.902*</td>
<td>1.129</td>
<td>111</td>
<td>78</td>
<td>.977</td>
<td>.036 (.025 - .047)</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td><strong>Metric</strong></td>
<td>172.181*</td>
<td>1.131</td>
<td>117</td>
<td>72</td>
<td>.979</td>
<td>.034 (.023 - .045)</td>
<td>2.508</td>
<td>6</td>
<td>.001</td>
<td>-.002</td>
</tr>
<tr>
<td><strong>Strong</strong></td>
<td>201.462*</td>
<td>1.124</td>
<td>123</td>
<td>66</td>
<td>.969</td>
<td>.040 (.030 - .050)</td>
<td>32.063*</td>
<td>6</td>
<td>-.009</td>
<td>.006</td>
</tr>
<tr>
<td><strong>Strict</strong></td>
<td>233.825*</td>
<td>1.134</td>
<td>132</td>
<td>57</td>
<td>.960</td>
<td>.044 (.035 - .053)</td>
<td>30.434*</td>
<td>9</td>
<td>-.009</td>
<td>.004</td>
</tr>
<tr>
<td><strong>Factor variance/covariance</strong></td>
<td>238.730*</td>
<td>1.133</td>
<td>138</td>
<td>51</td>
<td>.961</td>
<td>.043 (.033 - .052)</td>
<td>4.815</td>
<td>6</td>
<td>.000</td>
<td>-.001</td>
</tr>
<tr>
<td><strong>Factor means</strong></td>
<td>251.620*</td>
<td>1.131</td>
<td>141</td>
<td>48</td>
<td>.957</td>
<td>.044 (.035 - .053)</td>
<td>13.535*</td>
<td>3</td>
<td>-.004</td>
<td>.001</td>
</tr>
</tbody>
</table>

*Note.* $n = 400$. $\chi^2_c$ = scaling correction factor for $\chi^2$; $df =$ degrees of freedom; #fp = number of parameters estimated in each model; CFI = comparative fit index; RMSEA = root mean square error of approximation; $\Delta\chi^2$ = Satorra-Bentler scaled $\chi^2$ difference statistic; $\Delta\chi^2 df =$ degrees of freedom for Satorra-Bentler $\Delta\chi^2$; $\Delta$CFI = change in CFI estimate from less restricted to more restricted models (i.e., change in CFI from configural invariance model to metric invariance model); $\Delta$RMSEA = change in RMSEA estimate from less restricted to more restricted model. *$p < .001.$
The remaining steps of the MI analyses of the SDT measure provided further evidence of invariance across timepoints. Constraining the factor variances and covariances to equality across timepoints was not found to decrease model fit significantly, $\Delta \chi^2(6) = 4.815, p = .568$. Assessing invariance of the latent factor means revealed a significant $\Delta \chi^2$ test suggesting a decrease in model fit, $\Delta \chi^2(3) = 13.535, p < .005$. However, according to the $\Delta$CFI and $\Delta$RMSEA assessments the factor means also demonstrated equivalence, $\Delta$CFI = -.004 and $\Delta$RMSEA = .001. In sum, the SDT need satisfaction measure, and its constituent facets of autonomy, competence, and relatedness, demonstrated strong evidence of equivalence across timepoints, thus facilitating meaningful interpretations and additional analyses.

**Psychological well-being.** Table A9 documents the results of the MI tests of the PWB measure used in this study. As with the SDT analyses, the configural invariance model appeared to fit the data quite well, exhibiting a non-significant $\chi^2(5) = 5.490, p = .359$, and CFI and RMSEA estimates of .999 and .016, respectively. Throughout the MI analyses conducted, up to the test of equivalent latent means, none of the equality constraints significantly impacted model-data fit, according to the $\Delta \chi^2$ test. In particular, adding equality constraints on the factor loadings across timepoints for the metric invariance step resulted in a $\Delta \chi^2(2) = 4.969, p = .083$. Additionally including the equality constraints for equal means across respective item parcels resulted in $\Delta \chi^2(2) = 1.734, p = .421$. Adding the equality constraints across residual variances to assess strict invariance also did not significantly decrease model fit, $\Delta \chi^2(3) = 1.529, p = .676$. The factor variance was also found to be equivalent across timepoints, $\Delta \chi^2(1) = 3.107, p = .078$. Therefore, the factor loadings, item parcel means, item parcel residuals, provide evidence of invariance across timepoints as the $\Delta \chi^2$ test was not significant. The latent mean of the PWB variable, however, was found to be significantly lower at Time 2 than Time 1 ($\mu_{\text{Time2}} = -.281, p$
Table A13  

**Psychological Well-Being Longitudinal Measurement Invariance Analyses**

<table>
<thead>
<tr>
<th></th>
<th>$\chi^2$</th>
<th>$\chi^2_c$</th>
<th>$\chi^2 df$</th>
<th>#fp</th>
<th>CFI</th>
<th>RMSEA</th>
<th>$\Delta \chi^2$</th>
<th>$\Delta \chi^2 df$</th>
<th>$\Delta$CFI</th>
<th>$\Delta$RMSEA</th>
</tr>
</thead>
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<tr>
<td>Configural</td>
<td>5.490</td>
<td>1.096</td>
<td>5</td>
<td>22</td>
<td>.999</td>
<td>.016 (.000 - .073)</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Metric</td>
<td>10.183</td>
<td>1.054</td>
<td>7</td>
<td>20</td>
<td>.996</td>
<td>.034 (.000 - .075)</td>
<td>4.969</td>
<td>2</td>
<td>-.003</td>
<td>.018</td>
</tr>
<tr>
<td>Strong</td>
<td>11.919</td>
<td>1.053</td>
<td>9</td>
<td>18</td>
<td>.996</td>
<td>.028 (.000 - .067)</td>
<td>1.734</td>
<td>2</td>
<td>.000</td>
<td>-.006</td>
</tr>
<tr>
<td>Strict</td>
<td>13.126</td>
<td>1.102</td>
<td>12</td>
<td>15</td>
<td>.999</td>
<td>.015 (.000 - .054)</td>
<td>1.529</td>
<td>3</td>
<td>.002</td>
<td>-.013</td>
</tr>
<tr>
<td>Factor variance/</td>
<td>16.392</td>
<td>1.109</td>
<td>13</td>
<td>14</td>
<td>.996</td>
<td>.026 (.000 - .059)</td>
<td>3.107</td>
<td>1</td>
<td>-.003</td>
<td>.011</td>
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<tr>
<td>covariance</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
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<td></td>
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<tr>
<td>Factor means</td>
<td>45.434*</td>
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<td>14</td>
<td>13</td>
<td>.962</td>
<td>.075 (.051 - .100)</td>
<td>51.428*</td>
<td>1</td>
<td>-.034</td>
<td>.049</td>
</tr>
</tbody>
</table>

*Note. n = 400. $\chi^2_c$ = scaling correction factor for $\chi^2$; df = degrees of freedom; #fp = number of parameters estimated in each model; CFI = comparative fit index; RMSEA = root mean square error of approximation; $\Delta \chi^2$ = Satorra-Bentler scaled $\chi^2$ difference statistic; $\Delta \chi^2 df$ = degrees of freedom for Satorra-Bentler $\Delta \chi^2$; $\Delta$CFI = change in CFI estimate from less restricted to more restricted models (i.e., change in CFI from configural invariance model to metric invariance model); $\Delta$RMSEA = change in RMSEA estimate from less restricted to more restricted model. * $p < .001$. 
< .001; note that μ_{Time1} was fixed at zero for identification purposes), as demonstrated by Δχ^2(1) = 51.428, p < .001, ΔCFI = -.034, and ΔRMSEA = .049. Despite the final step in this MI analysis, the PWB scale did exhibit evidence of invariance across timepoints, thus facilitating its interpretation and use in longitudinal models and Hypothesis 1.1, which proposed to gain evidence supporting the construct validity of the SDT profiles.

**Psychological Capital.** Unlike the previous MI analyses, which were all focused on single-level constructs, PsyCap relies on a second-order factor model (Alessandri, Borgogni, Consiglio, & Mitidieri, 2015; Avey, Luthans, & Youssef, 2010). This is because, as discussed above, PsyCap relies upon the combined functioning of Hope, Self-Efficacy, Optimism, and Resiliency facets. This type of factor analysis includes a higher-order latent factor to account for the covariation between the lower-level latent facets (F. F. Chen, Sousa, & West, 2005; Cheung, 2008; Credé & Harms, 2015). There are two stages to demonstrate MI of a second-order measurement model. In keeping with the recommendations from Byrne and Stewart (2006), F. F. Chen et al. (2005), and Cheung (2008) invariance of the first-order structure was assessed prior to imposing equality constraints on the second-order factor loadings, means, and residual variances.

Table A10 presents the results of the MI analyses focused on the PsyCap measure. The initial configural invariance model provided an acceptable estimate of model fit, $\chi^2(227) = 367.729, p < .001, \text{CFI} = .959, \text{RMSEA} = .039 (90\% \text{ CI} = .032 - .047)$. Adding equality constraints across the factor loadings of facets on the item parcels across timepoints did not significantly decrease model fit $Δ\chi^2(8) = 7.095, p = .526$. Thus, the first-order factor loadings were equivalent across repeated measures. Next, adding equality constraints on the respective first-order item parcel means also did not significantly impact the model-data fit, $Δ\chi^2(8) =$
<table>
<thead>
<tr>
<th>Psychological Capital (PsyCap) Longitudinal Measurement Invariance Analyses</th>
<th>( \chi^2 )</th>
<th>( \chi^2c )</th>
<th>( \chi^2 ) df</th>
<th>#fp</th>
<th>CFI</th>
<th>RMSEA</th>
<th>( \Delta \chi^2 )</th>
<th>( \Delta \chi^2 ) df</th>
<th>( \Delta \text{CFI} )</th>
<th>( \Delta \text{RMSEA} )</th>
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</thead>
<tbody>
<tr>
<td>1(^{st}) order Configural</td>
<td>367.729***</td>
<td>1.145</td>
<td>227</td>
<td>97</td>
<td>.959</td>
<td>.039 (.032 - .047)</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>1(^{st}) order Metric</td>
<td>375.364***</td>
<td>1.141</td>
<td>235</td>
<td>89</td>
<td>.959</td>
<td>.039 (.031 - .046)</td>
<td>7.095</td>
<td>8</td>
<td>.000</td>
<td>.000</td>
</tr>
<tr>
<td>1(^{st}) order Strong</td>
<td>390.203***</td>
<td>1.136</td>
<td>243</td>
<td>81</td>
<td>.957</td>
<td>.039 (.032 - .046)</td>
<td>15.145</td>
<td>8</td>
<td>-.002</td>
<td>.000</td>
</tr>
<tr>
<td>1(^{st}) order Strict, 2(^{nd}) order Configural</td>
<td>401.171***</td>
<td>1.140</td>
<td>255</td>
<td>69</td>
<td>.957</td>
<td>.038 (.031 - .045)</td>
<td>11.544</td>
<td>12</td>
<td>.000</td>
<td>-.001</td>
</tr>
<tr>
<td>2(^{nd}) order Metric</td>
<td>410.193***</td>
<td>1.143</td>
<td>258</td>
<td>66</td>
<td>.956</td>
<td>.038 (.031 - .045)</td>
<td>8.417*</td>
<td>3</td>
<td>-.002</td>
<td>.000</td>
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<tr>
<td>2(^{nd}) order Strong</td>
<td>423.671***</td>
<td>1.140</td>
<td>261</td>
<td>63</td>
<td>.953</td>
<td>.039 (.032 - .046)</td>
<td>15.603**</td>
<td>3</td>
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<td>.001</td>
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<tr>
<td>2(^{nd}) order Strict</td>
<td>426.858***</td>
<td>1.143</td>
<td>265</td>
<td>59</td>
<td>.953</td>
<td>.039 (.032 - .046)</td>
<td>3.724</td>
<td>4</td>
<td>.000</td>
<td>.000</td>
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<tr>
<td>2(^{nd}) order Factor variance/covariance</td>
<td>431.685***</td>
<td>1.144</td>
<td>266</td>
<td>58</td>
<td>.952</td>
<td>.039 (.033 - .046)</td>
<td>4.272*</td>
<td>1</td>
<td>-.001</td>
<td>.000</td>
</tr>
<tr>
<td>2(^{nd}) order Factor means</td>
<td>434.054***</td>
<td>1.144</td>
<td>267</td>
<td>57</td>
<td>.951</td>
<td>.040 (.033 - .046)</td>
<td>2.467</td>
<td>1</td>
<td>-.001</td>
<td>.001</td>
</tr>
</tbody>
</table>

**Note.** \( n = 400. \chi^2c = \text{scaling correction factor for } \chi^2; \) df = degrees of freedom; #fp = number of parameters estimated in each model; CFI = comparative fit index; RMSEA = root mean square error of approximation; \( \Delta \chi^2 = \text{Satorra-Bentler scaled } \chi^2 \text{ difference statistic}; \) \( \Delta \chi^2 \) df = degrees of freedom for Satorra-Bentler \( \Delta \chi^2 \); \( \Delta \text{CFI} = \text{change in CFI estimate from less restricted to more restricted models (i.e., change in CFI from configural invariance model to metric invariance model)}; \) \( \Delta \text{RMSEA} = \text{change in RMSEA estimate from less restricted to more restricted model. Second-order configural invariance model was based on the first-order strict invariance model.} * p < .05, ** p < .01, *** p < .001. **
15.145, \( p = .056 \) (in this case, as the \( p \)-value is approaching that of statistical significance, it may be noteworthy to also compare the \( \Delta \text{CFI} \) and \( \Delta \text{RMSEA} \) estimates: -.002 and .000, respectively). Thus, the item parcel means were also found to be equivalent across timepoints. Adding equality constraints over the residual variances of the item parcels was also found to not significantly decrease the model fit, \( \Delta \chi^2(12) = 11.544, p = .483 \).

After determining the measurement invariant properties, up to the stage of strict invariance, the MI analyses focus on the second-order structure (see e.g., Cheung, 2008). Building upon the equality constraints imposed upon the residual variances of the item parcels, additional constraints were imposed on the second-order factor loadings, which had previously been free to vary across timepoints in the previous analyses. These additional equality constraints resulted in a significant decrease in fit according to the \( \Delta \chi^2 \) test, \( \Delta \chi^2(3) = 8.417, p < .050 \), but not the \( \Delta \text{CFI} \) and \( \Delta \text{RMSEA} \) guidelines, -.002 and .000, respectively. Therefore, despite a significant change in \( \chi^2 \) value for the second-order metric invariance step, the estimates provided by the \( \Delta \text{CFI} \) and \( \Delta \text{RMSEA} \) tests suggests that the factor loadings for PsyCap on the Hope, Self-Efficacy, Resiliency, and Optimism facets are equivalent across timepoints.

As in the single-level MI tests, after demonstrating the equivalence of the second-order factor loadings, the next step is to investigate the invariance of the second-order means. Second-order strong invariance therefore examines whether the latent means of the Hope, Self-Efficacy, Resiliency, and Optimism facets are similar across timepoints. Imposing these additional constraints resulted in a \( \Delta \chi^2(3) = 15.603, p < .005 \), suggesting that the means of the facets were different across assessments. On the other hand, according to the \( \Delta \text{CFI} \) and \( \Delta \text{RMSEA} \) tests, strong invariance of the second-order factor model was supported, \( \Delta \text{CFI} = -.003, \Delta \text{RMSEA} \)...
RESILIENCY AND WELL-BEING

Taken together, support was found for strong invariance of PsyCap’s first-order latent facet means across repeated measures. Including additional constraints over the equality of the second-order residual variances (variances of the latent facets) was not found to significantly decrease model-data fit, as $\Delta \chi^2(4) = 3.724$, $p = .445$, thus suggesting that the variances of the facets were equivalent across timepoints. On the other hand, in the subsequent MI step, the variance of the latent PsyCap variable was found to vary across timepoints, $\Delta \chi^2(1) = 4.272$, $p < .05$. However, this was not reflected by changes in the CFI and RMSEA estimates, -.001 and .001, respectively. Therefore, invariance of the second-order PsyCap latent variance estimates was supported. Finally, the latent mean of the second-order PsyCap factor was tested for equivalence across timepoints. This resulted in a $\Delta \chi^2(1) = 2.467$, $p = .116$, and a $\Delta$CFI = -.001, and a $\Delta$RMSEA = .001. This would suggest that once constraining the latent first-order facet means of Hope, Self-Efficacy, Resilience, and Optimism to equality across timepoints, there was no longer a significant difference between PsyCap latent means across timepoints.

Taken together, these analyses support the full invariance of the PsyCap measure, and its second-order factor model, across Time 1 and Time 2 assessments. These results allow for readily interpretable comparisons of PsyCap over time, and support the longitudinal validity of the PsyCap (Ployhart & Vandenberg, 2010; Siu et al., 2009).

**Workplace Resiliency Inventory.** First, as shown in Table A11, the configural invariant model displayed adequate estimates of model-data fit with a $\chi^2(936) = 1,435.022$, $p < .01$, CFI = .954, RMSEA = .037 (90% CI = .033 - .040). Adding equality constraints on the factor loadings did not significantly reduce model fit as $\Delta \chi^2(16) = 11.131$, $p = .801$. As well, changes in the CFI and RMSEA estimates were not suggestive of significant differences of the factor
<table>
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<th>Model</th>
<th>$\chi^2$</th>
<th>$\chi^2_c$</th>
<th>$\chi^2 df$</th>
<th>#fp</th>
<th>CFI</th>
<th>RMSEA</th>
<th>$\Delta\chi^2$</th>
<th>$\Delta\chi^2 df$</th>
<th>$\Delta$CFI</th>
<th>$\Delta$RMSEA</th>
</tr>
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<tbody>
<tr>
<td>Configural</td>
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<td>936</td>
<td>288</td>
<td>.954</td>
<td>.037 (.033 - .040)</td>
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<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Metric</td>
<td>1444.471**</td>
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<td>952</td>
<td>272</td>
<td>.954</td>
<td>.036 (.032 - .040)</td>
<td>11.131</td>
<td>16</td>
<td>.001</td>
<td>-.001</td>
</tr>
<tr>
<td>Strong</td>
<td>1485.934**</td>
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<td>968</td>
<td>256</td>
<td>.952</td>
<td>.037 (.033 - .040)</td>
<td>43.141**</td>
<td>16</td>
<td>-.002</td>
<td>.001</td>
</tr>
<tr>
<td>Strict</td>
<td>1522.417**</td>
<td>1.088</td>
<td>992</td>
<td>232</td>
<td>.951</td>
<td>.037 (.033 - .040)</td>
<td>36.626*</td>
<td>24</td>
<td>-.001</td>
<td>.000</td>
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<tr>
<td>Factor variance/</td>
<td>1576.676**</td>
<td>1.089</td>
<td>1028</td>
<td>196</td>
<td>.949</td>
<td>.037 (.033 - .040)</td>
<td>54.281*</td>
<td>36</td>
<td>-.002</td>
<td>.000</td>
</tr>
<tr>
<td>covariance</td>
<td>Factor means</td>
<td>1616.557**</td>
<td>1.088</td>
<td>1036</td>
<td>188</td>
<td>.946</td>
<td>.037 (.034 - .041)</td>
<td>43.164**</td>
<td>8</td>
<td>-.003</td>
</tr>
</tbody>
</table>

Note. $n = 400$. $\chi^2_c$ = scaling correction factor for $\chi^2$; $df$ = degrees of freedom; #fp = number of parameters estimated in each model; CFI = comparative fit index; RMSEA = root mean square error of approximation; $\Delta\chi^2$ = Satorra-Bentler scaled $\chi^2$ difference statistic; $\Delta\chi^2 df$ = degrees of freedom for Satorra-Bentler $\Delta\chi^2$; $\Delta$CFI = change in CFI estimate from less restricted to more restricted models (i.e., change in CFI from configural invariance model to metric invariance model); $\Delta$RMSEA = change in RMSEA estimate from less restricted to more restricted model. * $p < .05$, ** $p < .001$. 
loadings across timepoints, $\Delta \text{CFI} = -.001$, and $\Delta \text{RMSEA} = -.001$. Interestingly, the decrease in RMSEA would actually suggest an improvement in fit of the metric invariance model over the configural invariance model, such that the more parsimonious model defined by the metric invariance model led to a better overall fitting model (Marsh et al., 2005).

Implementing the invariance constraints for equal item parcel intercepts, over and above the metric invariance constraints, resulted in a significant $\Delta \chi^2(16) = 43.141, p < .001$. In light of this, however, examining the $\Delta \text{CFI}$ and $\Delta \text{RMSEA}$ suggests weak evidence of non-invariance. The CFI decreased by .002 to .952, and the RMSEA increased by .001 to .037, both of which are considerably lower than the MI guidelines. The test of strict invariance, in which the respective residual variances of each item parcel were constrained to equality across timepoints also demonstrated a significant decreases in fit, $\Delta \chi^2(24) = 36.626, p < .050$. However, like previous analyses that provided a statistically significant $\Delta \chi^2$ test result across more constrained models, the addition of the residual variance equality constraints did not suggest non-invariance according to the $\Delta \text{CFI}$ and $\Delta \text{RMSEA}$ guidelines, -.001 and .000, respectively.

For the next stage of the MI analyses of the WRI, additional equality constraints were imposed upon the factor variances and covariances across the two timepoints. In comparing this model to the strict invariance model suggested a significant decrease in fit, $\Delta \chi^2(36) = 54.281, p < .050$. On the other hand, the change in CFI and RMSEA estimates were trivial: -.002 and .000, respectively. Thus, the WRI’s latent factor variances and covariances were found to be equivalent across timepoints.

The final stage of the MI analyses for the WRI constrained the latent means to equality across timepoints. These additional equality constraints significantly decreased fit according to
the $\Delta \chi^2$ test, such that $\Delta \chi^2(8) = 43.164, p < .001$. However, considering the $\Delta$CFI and $\Delta$RMSEA (-.003 and .000, respectively) indices suggests that invariance is supported.
Appendix L – LPA Invariance Results

Appendix E laid out the necessary steps to investigate the invariance of LPA solutions across time (and could easily be applied to across group contexts [i.e., across men and women, or across national groups]). Table A12 provides the results of LPA invariance analyses. Configural invariance was supported in that three profiles was deemed to be the optimal number of profiles recovered in both the Time 1 and Time 2 SDT need satisfaction assessments. As such, the configural invariance model can be used as a baseline upon which to test the equality of the constraints of the structural invariance model. Imposing the constraints of structural invariance (i.e., an equality constrain over the mean of autonomy within the Time 1 and Time 2 Low profiles) resulted in a significant decrease in fit according to the LRT, $\Delta \chi^2(9) = 63.904, p < .001$. However, the BIC demonstrated a decrease between the configural and structural invariance models. Thus, with an emphasis on the BIC estimates (in accordance with Hoferichter et al., 2014), the structural invariance of the Time 1 and Time 2 LPA models is supported.

Next, based on the structural invariance model, I added the constraints specified by dispersionsal invariance (i.e., the residual variance of Competence is estimated to be equal in both Moderate profiles recovered at Time 1 and Time 2). According to the LRT, these additional constraints significantly decreased model fit, $\Delta \chi^2(9) = 45.556, p < .001$. However, examining the BIC (and the other information criteria) suggested that model-data fit was superior in the dispersionsal invariance model than the structural invariance model. Accordingly, dispersionsal invariance was supported across timepoints.

Lastly, the distributional invariance model, in which additional equality constraints were imposed upon profile threshold parameters to constrain the relative size of the profiles to equivalence, was estimated. Compared to the dispersionsal invariance model, the LRT, $\Delta \chi^2(2) = \ldots$
Table A16

**Latent Profile Invariance**

<table>
<thead>
<tr>
<th></th>
<th>LL</th>
<th>LLc</th>
<th>#fp</th>
<th>AIC</th>
<th>CAIC</th>
<th>BIC</th>
<th>aBIC</th>
<th>LRT</th>
<th>df</th>
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</thead>
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<tr>
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<td>-1135.642</td>
<td>1.226</td>
<td>44</td>
<td>2359.284</td>
<td>2386.822</td>
<td>2535.018</td>
<td>2395.403</td>
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<td>--</td>
</tr>
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<td>35</td>
<td>2372.580</td>
<td>2394.690</td>
<td>2512.369</td>
<td>2401.311</td>
<td>63.904*</td>
<td>9</td>
</tr>
<tr>
<td>Dispersional</td>
<td>-1160.139</td>
<td>1.771</td>
<td>26</td>
<td>2372.277</td>
<td>2388.960</td>
<td>2476.120</td>
<td>2393.620</td>
<td>45.556*</td>
<td>9</td>
</tr>
<tr>
<td>Distributional</td>
<td>-1196.734</td>
<td>1.797</td>
<td>24</td>
<td>2441.469</td>
<td>2456.943</td>
<td>2537.324</td>
<td>2461.170</td>
<td>50.386*</td>
<td>2</td>
</tr>
</tbody>
</table>

*Note.* LL = model loglikelihood; LLc = scaling correction factor for loglikelihood; #fp = number of parameters estimated in each model; LRT = likelihood ratio test statistic, computed using LLc and Satorra-Bentler (Satorra & Bentler, 2001) correction; df = degrees of freedom for each LRT. *LRT is not available for the configural invariance model, as it serves as the baseline for the structural invariance model. *p < .001.*
50.386, $p < .001$, and the BIC (and other information criteria) suggested a substantial degree of misfit. Thus, distributional invariance can not be supported across timepoints.

In particular, at Time 1 34.9% of the participants were classified into the High profile, 45.9% were in the Moderate profile, and 19.2% were in the Low profile. At Time 2, however, only 11.2% of the participants remained in the High profile, whereas 38.2% were classified into the Moderate profile, and 50.6% were in the Low profile. Thus, despite similar mean levels, as supported by the scalar invariance of the SDT CFAs and the structural invariance documented here, there is a strong downward trend in membership in the SDT profiles over time. Therefore, Hypothesis 1.3 was supported. The next stage in my analyses is to investigate the transitions that occurred between Time 1 and Time 2 profiles.
Appendix M – Latent Transition Analysis Specifications

There were two major aspects I considered prior to examining the LTA models involved with the current study. First off, as indicated by the non-perfect entropy estimates, there is some degree of classification inaccuracy, or unreliability, in determining profile membership. This suggests that a non-trivial proportion of boundary cases (see Kam et al., in press for their discussion of boundary cases) may be misclassified and may bias overall model results. As such, I used Nylund-Gibson et al.’s (2014) method of maintaining profile membership in mixture models that involve complex models with more than one latent categorical variable. This was essential because explicitly including additional variables in a LPA (i.e., outcome or predictor variables) can substantially change the fit and estimates of a model. Nylund-Gibson et al.’s procedure allows for new variables to be included in the model, but will not impact the overall membership probabilities. This provides an unbiased estimate of the Time 1 → Time 2 transitions present.

Additionally, in light of the evidence suggesting that no participants improved their profile status, I drew upon the LTA parameterization from Kaplan (2008). Kaplan provided directions on the derivation of an LTA when there were no downward transitions. (Of note, Kaplan refers to a [hidden] Markov model; this does not reflect a substantial difference from the LTA model. The only difference consists of whether there is a single latent profile indicator, as in Markov models, or whether there are multiple indicators, as in LTAs.) This specification, because there were empty cells in the transition matrix (see Table 12), was necessary for this Study’s LTA models. Thus, I considered Kaplan’s recommendations, and those from B. O. Muthén and Asparouhov (2011), who provided the technical Mplus specifications necessary for identifying a model with empty transition probabilities. In particular, Muthén and Asparouhov
denoted the importance of using logit, rather than probability parameterization to estimate such a model. This means that membership thresholds are considered, rather than the more interpretable probabilities. Thus, considering a particular transition that was not supported by the data (i.e., Low<sup>Time 1</sup> → Moderate<sup>Time 2</sup>), it must be fixed to a logit that represents an extremely low probability, rather than dealing explicitly with the probability. L. K. Muthén and Muthén (2012) and J. Wang and Wang (2012) considered a logit value of -15.000 to be of an extremely low probability (which can be translated into a probability by $e^{-15} = 3.059 \times 10^{-7}$).

Without fixing parameters in the transition matrix, this LTA did not converge properly and resulted in numerous out-of-bounds parameters. Further, fixing these empty transition probabilities was warranted upon several empirical grounds. For example, Chung, Anthony, and Schafer (2011) argued that parameters that are not empirically identified (as is the case when no individuals made positive transitions) should be fixed at a particular, theoretically appropriate value so that the permissible estimates for identified parameters may be achieved. Implementing a LTA model with the empty transitions fixed to low logit values converged normally, and resulted in permissible parameter estimates. Thus, the current study’s LTA used a parameterization informed by Nylund-Gibson et al.’s (2014) treatment of classification errors in combination with Kaplan’s (2008) specifications in the presence of empty transitions.
Appendix N – Mover-Stayer Differences Across Time 1 and Time 2 Variables

Table A17

<table>
<thead>
<tr>
<th></th>
<th>Time 1</th>
<th>Time 2</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mover</td>
<td>Stayer</td>
<td>Mover</td>
</tr>
<tr>
<td>PC-A</td>
<td>3.153 (.671)</td>
<td>3.239 (.677)</td>
<td>3.088 (.668)*</td>
</tr>
<tr>
<td>PC-B</td>
<td>3.968 (.477)</td>
<td>4.046 (.487)</td>
<td>3.776 (.541)***</td>
</tr>
<tr>
<td>PC-C</td>
<td>3.380 (.648)</td>
<td>3.400 (.694)</td>
<td>3.253 (.695)</td>
</tr>
<tr>
<td>OSR</td>
<td>4.443 (.681)*</td>
<td>4.629 (.563)</td>
<td>4.467 (.624)*</td>
</tr>
<tr>
<td>IR</td>
<td>2.554 (.613)</td>
<td>2.445 (.578)</td>
<td>2.760 (.564)***</td>
</tr>
<tr>
<td>SRP-A</td>
<td>3.411 (.636)</td>
<td>3.435 (.655)</td>
<td>3.371 (.613)</td>
</tr>
<tr>
<td>SRP-B</td>
<td>3.098 (.618)</td>
<td>3.208 (.683)</td>
<td>2.974 (.610)**</td>
</tr>
<tr>
<td>SRP-C</td>
<td>3.142 (.623)***</td>
<td>3.447 (.595)</td>
<td>2.877 (.612)***</td>
</tr>
<tr>
<td>PsyCap</td>
<td>3.611 (.401)*</td>
<td>3.728 (.385)</td>
<td>3.516 (.391)***</td>
</tr>
</tbody>
</table>

Note. $n = 323$. Standard deviations in parentheses. ANOVA tests of significance presented for within timepoint comparisons across Movers and Stayers. * $p < .05$, ** $p < .01$, *** $p < .001$. 


Appendix O – Mover-Stayer Correlations

Table A18

Correlation Matrix of PWB and Resiliency Variables in Mover-Stayer Model

<table>
<thead>
<tr>
<th></th>
<th>1</th>
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<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
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<tbody>
<tr>
<td>1</td>
<td>MS</td>
<td>--</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>PC-A</td>
<td>.147</td>
<td>--</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>PC-B</td>
<td>.234</td>
<td>.284</td>
<td>--</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>PC-C</td>
<td>.158</td>
<td>.350</td>
<td>.412</td>
<td>--</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>OSR</td>
<td>-.006</td>
<td>.062</td>
<td>.245</td>
<td>-.040</td>
<td>--</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>IR</td>
<td>-.228</td>
<td>-.428</td>
<td>-.264</td>
<td>-.302</td>
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<td>--</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>SRP-A</td>
<td>.068</td>
<td>.186</td>
<td>.364</td>
<td>.202</td>
<td>.065</td>
<td>-.140</td>
<td>--</td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>SRP-B</td>
<td>.147</td>
<td>.437</td>
<td>.643</td>
<td>.343</td>
<td>.037</td>
<td>-.344</td>
<td>.383</td>
<td>--</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>SRP-C</td>
<td>.165</td>
<td>.578</td>
<td>.371</td>
<td>.377</td>
<td>.159</td>
<td>-.604</td>
<td>.116</td>
<td>.575</td>
<td>--</td>
</tr>
<tr>
<td>10</td>
<td>PWB</td>
<td>.279</td>
<td>.240</td>
<td>.483</td>
<td>.219</td>
<td>.290</td>
<td>-.184</td>
<td>.173</td>
<td>.273</td>
<td>.307</td>
</tr>
</tbody>
</table>

Note. $n = 323$. MS = Mover-Stayer categorization (1 = Mover, 2 = Stayer; Low-Low Stayers omitted); PC-A = Personal Characteristics – Affective; PC-B = Personal Characteristics – Behavioral; PC-C = Personal Characteristics – Cognitive; IR = Initial Response; OSR = Opportunities, Supports, and Resources; SRP-A = Self-Regulatory Processes – Affective; SRP-B = Self-Regulatory Processes – Behavioral; SRP-C = Self-Regulatory Processes – Cognitive; PWB = psychological well-being. Correlations greater than $|.|11| p < .05$, greater than $|.|15| p < .01$. 
Appendix P – Study 2 ethics approval

Department of Psychology
The University of Western Ontario
Room 7418 Social Sciences Centre,
London, ON, Canada N6A 5C1
Telephone: (519) 867-6567 Fax: (519) 866-3961

Use of Human Subjects - Ethics Approval Notice

<table>
<thead>
<tr>
<th>Review Number</th>
<th>13 03 25</th>
<th>Approval Date</th>
<th>13 03 14</th>
</tr>
</thead>
<tbody>
<tr>
<td>Principal Investigator</td>
<td>Mitch Rothstein/Matt McLarnon</td>
<td>End Date</td>
<td>14 04 30</td>
</tr>
<tr>
<td>Protocol Title</td>
<td>Coping through the re-employment process</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sponsor</td>
<td>n/a</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

This is to notify you that The University of Western Ontario Department of Psychology Research Ethics Board (PREB) has granted expedited ethics approval to the above named research study on the date noted above.

The PREB is a sub-REB of The University of Western Ontario’s Research Ethics Board for Non-Medical Research Involving Human Subjects (NMREB) which is organized and operates according to the Tri-Council Policy Statement and the applicable laws and regulations of Ontario. (See Office of Research Ethics web site: http://www.uwo.ca/research/ethics/)

This approval shall remain valid until end date noted above assuming timely and acceptable responses to the University’s periodic requests for surveillance and monitoring information.

During the course of the research, no deviations from, or changes to, the protocol or consent form may be initiated without prior written approval from the PREB except when necessary to eliminate immediate hazards to the subject or when the change(s) involve only logistical or administrative aspects of the study (e.g. change of research assistant, telephone number etc). Subjects must receive a copy of the information/consent documentation.

Investigators must promptly also report to the PREB:

a) changes increasing the risk to the participant(s) and/or affecting significantly the conduct of the study;

b) all adverse and unexpected experiences or events that are both serious and unexpected;

c) new information that may adversely affect the safety of the subjects or the conduct of the study.

If these changes/adverse events require a change to the information/consent documentation, and/or recruitment advertisement, the newly revised information/consent documentation, and/or advertisement, must be submitted to the PREB for approval.

Members of the PREB who are named as investigators in research studies, or declare a conflict of interest, do not participate in discussion related to, nor vote on, such studies when they are presented to the PREB.

Clive Seligman Ph.D.
Chair, Psychology Expedited Research Ethics Board (PREB)

The other members of the 2012-2013 PREB are: Mike Atkinson (Introductory Psychology Coordinator), Rick Goffin, Riley Hinson, Albert Katz (Department Chair), Steve Lupker, and Adam Piraino (Graduate Student Representative)

CC: UWO Office of Research Ethics

This is an official document. Please retain the original in your files.
Appendix Q – Priming scenario for Study 2

Take yourself back to the day when you were notified of your job loss. In the space below, please briefly describe ‘what happened,’ and what you thought and felt about it, as if you were telling this to a close friend.
Appendix R – Job Search Self-Efficacy Questionnaire

<table>
<thead>
<tr>
<th></th>
<th>A: Strongly Agree</th>
<th>B: Disagree</th>
<th>C: Neither Disagree nor Agree</th>
<th>D: Agree</th>
<th>E: Strongly Agree</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>When I make plans about my job search actions, I am certain I can make them work.</td>
<td>A B C D E</td>
<td>A B C D E</td>
<td>A B C D E</td>
<td>A B C D E</td>
</tr>
<tr>
<td>2.</td>
<td>I feel that I am strong enough to overcome the difficulties in the job search process.</td>
<td>A B C D E</td>
<td>A B C D E</td>
<td>A B C D E</td>
<td>A B C D E</td>
</tr>
<tr>
<td>3.</td>
<td>I feel that I can handle the situations that my job search will bring.</td>
<td>A B C D E</td>
<td>A B C D E</td>
<td>A B C D E</td>
<td>A B C D E</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>A: Not at all Confident</th>
<th>B: Moderately Confident</th>
<th>C: Totally Confident</th>
</tr>
</thead>
<tbody>
<tr>
<td>4.</td>
<td>Impressing interviewers during employment interviews.</td>
<td>A B C D E</td>
<td>A B C D E</td>
</tr>
<tr>
<td>5.</td>
<td>Obtaining more than one good job offer.</td>
<td>A B C D E</td>
<td>A B C D E</td>
</tr>
<tr>
<td>7.</td>
<td>Preparing a persuasive statement of why you should be considered for a job that will attract the interest of employers.</td>
<td>A B C D E</td>
<td>A B C D E</td>
</tr>
<tr>
<td>8.</td>
<td>Finding out where job openings exist.</td>
<td>A B C D E</td>
<td>A B C D E</td>
</tr>
<tr>
<td>9.</td>
<td>Preparing resumes that will get you job interviews.</td>
<td>A B C D E</td>
<td>A B C D E</td>
</tr>
</tbody>
</table>
Appendix S – Study 2 Sensitivity Analyses, Measurement Invariance

Table A19

_Longitudinal Measurement Invariance Analysis of the WRI’s PC-A Facet_

<table>
<thead>
<tr>
<th></th>
<th>$\chi^2$</th>
<th>$\chi^2c$</th>
<th>$\chi^2 df$</th>
<th>#fp</th>
<th>CFI</th>
<th>RMSEA</th>
<th>$\Delta\chi^2$</th>
<th>$\Delta\chi^2 df$</th>
<th>$\Delta$CFI</th>
<th>$\Delta$RMSEA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Configural</td>
<td>45.799*</td>
<td>.618</td>
<td>15</td>
<td>39</td>
<td>.854</td>
<td>.176 (.119 - .236)</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Metric</td>
<td>37.195*</td>
<td>.838</td>
<td>19</td>
<td>35</td>
<td>.914</td>
<td>.120 (.061 - .178)</td>
<td>1.723</td>
<td>4</td>
<td>.060</td>
<td>-.056</td>
</tr>
<tr>
<td>Strong</td>
<td>44.189*</td>
<td>.853</td>
<td>23</td>
<td>31</td>
<td>.900</td>
<td>.118 (.064 - .170)</td>
<td>7.062</td>
<td>4</td>
<td>-.014</td>
<td>-.002</td>
</tr>
<tr>
<td>Strict</td>
<td>63.137*</td>
<td>.890</td>
<td>29</td>
<td>25</td>
<td>.839</td>
<td>.134 (.088 - .179)</td>
<td>17.942*</td>
<td>6</td>
<td>-.061</td>
<td>.016</td>
</tr>
<tr>
<td>Partial Strict</td>
<td>48.209*</td>
<td>.955</td>
<td>28</td>
<td>26</td>
<td>.904</td>
<td>.105 (.051 - .153)</td>
<td>5.850</td>
<td>5</td>
<td>.005</td>
<td>-.013</td>
</tr>
<tr>
<td>Factor variance/covariance</td>
<td>48.870*</td>
<td>.965</td>
<td>30</td>
<td>24</td>
<td>.911</td>
<td>.098 (.042 - .146)</td>
<td>1.014</td>
<td>2</td>
<td>.006</td>
<td>-.007</td>
</tr>
<tr>
<td>Factor means</td>
<td>54.908*</td>
<td>.972</td>
<td>32</td>
<td>22</td>
<td>.892</td>
<td>.104 (.054 - .150)</td>
<td>5.750</td>
<td>2</td>
<td>-.019</td>
<td>.006</td>
</tr>
</tbody>
</table>

*Note. n = 66. $\chi^2c$ = scaling correction factor for $\chi^2$; $df$ = degrees of freedom; #fp = number of parameters estimated in each model; CFI = comparative fit index; RMSEA = root mean square error of approximation; $\Delta\chi^2$ = Satorra-Bentler scaled $\chi^2$ difference statistic; $\Delta\chi^2 df$ = degrees of freedom for Satorra-Bentler $\Delta\chi^2$; $\Delta$CFI = change in CFI estimate from less restricted to more restricted models (i.e., change in CFI from configural invariance model to metric invariance model); $\Delta$RMSEA = change in RMSEA estimate from less restricted to more restricted model. The partial strict invariance model is compared to the strong invariance model. The factor variance/covariance and factor mean invariance models are more restrictive models than the partial strict invariance model. * $p < .05.$
### Table A20

**Longitudinal Measurement Invariance Analysis of the WRI’s PC-B Facet**

<table>
<thead>
<tr>
<th></th>
<th>$\chi^2$</th>
<th>$\chi^2c$</th>
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<th>#fp</th>
<th>CFI</th>
<th>RMSEA</th>
<th>$\Delta\chi^2$</th>
<th>$\Delta\chi^2 df$</th>
<th>$\Delta$CFI</th>
<th>$\Delta$RMSEA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Configural</td>
<td>36.144*</td>
<td>.915</td>
<td>15</td>
<td>39</td>
<td>.914</td>
<td>.146 (.086 - .208)</td>
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<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Metric</td>
<td>35.754*</td>
<td>.995</td>
<td>19</td>
<td>35</td>
<td>.932</td>
<td>.116 (.054 - .173)</td>
<td>1.938</td>
<td>4</td>
<td>.018</td>
<td>-.030</td>
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<tr>
<td>Strong</td>
<td>37.025*</td>
<td>.999</td>
<td>23</td>
<td>31</td>
<td>.943</td>
<td>.096 (.028 - .151)</td>
<td>1.382</td>
<td>4</td>
<td>.011</td>
<td>-.020</td>
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<td>Strict</td>
<td>39.575</td>
<td>1.174</td>
<td>29</td>
<td>25</td>
<td>.957</td>
<td>.074 (.000 - .128)</td>
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<td>.014</td>
<td>-.022</td>
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<tr>
<td>covariation</td>
<td>40.444</td>
<td>1.149</td>
<td>31</td>
<td>23</td>
<td>.961</td>
<td>.068 (.000 - .121)</td>
<td>.012</td>
<td>2</td>
<td>.005</td>
<td>-.006</td>
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<td>Factor means</td>
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<td>21</td>
<td>.965</td>
<td>.062 (.000 - .116)</td>
<td>.574</td>
<td>2</td>
<td>.004</td>
<td>-.006</td>
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</table>

*Note. n = 66. $\chi^2c = \text{scaling correction factor for } \chi^2; df = \text{degrees of freedom; #fp = number of parameters estimated in each model; CFI = comparative fit index; RMSEA = root mean square error of approximation; } \Delta\chi^2 = \text{Satorra-Bentler scaled } \chi^2 \text{ difference statistic; } \Delta\chi^2 df = \text{degrees of freedom for Satorra-Bentler } \Delta\chi^2; \Delta$CFI = change in CFI estimate from less restricted to more restricted models (i.e., change in CFI from configural invariance model to metric invariance model); $\Delta$RMSEA = change in RMSEA estimate from less restricted to more restricted model. * $p < .05.$*
Table A21

*Longitudinal Measurement Invariance Analysis of the WRI’s PC-C Facet*

<table>
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<tr>
<th>Model</th>
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<th>$\chi^2_c$</th>
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<th>#fp</th>
<th>CFI</th>
<th>RMSEA</th>
<th>$\Delta \chi^2$</th>
<th>$\Delta \chi^2_df$</th>
<th>$\Delta$CFI</th>
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<td>11.426</td>
<td>.956</td>
<td>15</td>
<td>39</td>
<td>1.000</td>
<td>.000 (.000 - .088)</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Metric</td>
<td>16.231</td>
<td>.935</td>
<td>19</td>
<td>35</td>
<td>1.000</td>
<td>.000 (.000 - .091)</td>
<td>4.969</td>
<td>4</td>
<td>.000</td>
<td>.000</td>
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<td>Strong</td>
<td>18.376</td>
<td>.941</td>
<td>23</td>
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<td>.000 (.000 - .075)</td>
<td>2.185</td>
<td>4</td>
<td>.000</td>
<td>.000</td>
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<tr>
<td>Strict</td>
<td>22.013</td>
<td>1.042</td>
<td>29</td>
<td>25</td>
<td>1.000</td>
<td>.000 (.000 - .059)</td>
<td>3.950</td>
<td>6</td>
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<td>.000</td>
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<td>Factor variance/covariance</td>
<td>23.661</td>
<td>1.016</td>
<td>31</td>
<td>23</td>
<td>1.000</td>
<td>.000 (.000 - .058)</td>
<td>1.725</td>
<td>2</td>
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<td>Factor means</td>
<td>25.545</td>
<td>1.024</td>
<td>33</td>
<td>21</td>
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<td>.000 (.000 - .057)</td>
<td>1.847</td>
<td>2</td>
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<td>.000</td>
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</table>

Note. $n = 66$. $\chi^2_c$ = scaling correction factor for $\chi^2$; $df = $ degrees of freedom; #fp = number of parameters estimated in each model; CFI = comparative fit index; RMSEA = root mean square error of approximation; $\Delta \chi^2 = $ Satorra-Bentler scaled $\chi^2$ difference statistic; $\Delta \chi^2_df = $ degrees of freedom for Satorra-Bentler $\Delta \chi^2$; $\Delta$CFI = change in CFI estimate from configural invariance model to metric invariance model; $\Delta$RMSEA = change in RMSEA estimate from less restricted to more restricted model. *p < .05.
Table A22

Longitudinal Measurement Invariance Analysis of the WRI’s OSR Facet

<table>
<thead>
<tr>
<th>Model Type</th>
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<th>$\chi^2_c$</th>
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<th>#fp</th>
<th>CFI</th>
<th>RMSEA</th>
<th>$\Delta\chi^2$</th>
<th>$\Delta\chi^2_{df}$</th>
<th>$\Delta$CFI</th>
<th>$\Delta$RMSEA</th>
</tr>
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<tbody>
<tr>
<td>Configurational</td>
<td>48.475*</td>
<td>.904</td>
<td>15</td>
<td>39</td>
<td>.940</td>
<td>.184</td>
<td>(.128 -.243)</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Metric</td>
<td>54.531*</td>
<td>.924</td>
<td>19</td>
<td>35</td>
<td>.936</td>
<td>.168</td>
<td>(.117 -.222)</td>
<td>6.572</td>
<td>4</td>
<td>-.004</td>
</tr>
<tr>
<td>Strong</td>
<td>56.464*</td>
<td>.909</td>
<td>23</td>
<td>31</td>
<td>.940</td>
<td>.148</td>
<td>(.100 -.198)</td>
<td>1.132</td>
<td>4</td>
<td>.004</td>
</tr>
<tr>
<td>Strict</td>
<td>64.937*</td>
<td>1.119</td>
<td>29</td>
<td>25</td>
<td>.935</td>
<td>.137</td>
<td>(.092 -.182)</td>
<td>11.090</td>
<td>6</td>
<td>-.004</td>
</tr>
<tr>
<td>Factor variance/covariance</td>
<td>67.928*</td>
<td>1.101</td>
<td>31</td>
<td>23</td>
<td>.933</td>
<td>.134</td>
<td>(.091 -.178)</td>
<td>2.546</td>
<td>2</td>
<td>-.002</td>
</tr>
<tr>
<td>Factor means</td>
<td>69.267*</td>
<td>1.096</td>
<td>33</td>
<td>21</td>
<td>.935</td>
<td>.129</td>
<td>(.086 -.172)</td>
<td>1.092</td>
<td>2</td>
<td>.001</td>
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</table>

*Note. n = 66. $\chi^2_c$ = scaling correction factor for $\chi^2$; $df$ = degrees of freedom; #fp = number of parameters estimated in each model; CFI = comparative fit index; RMSEA = root mean square error of approximation; $\Delta\chi^2$ = Satorra-Bentler scaled $\chi^2$ difference statistic; $\Delta\chi^2_{df}$ = degrees of freedom for Satorra-Bentler $\Delta\chi^2$; $\Delta$CFI = change in CFI estimate from less restricted to more restricted models (i.e., change in CFI from configural invariance model to metric invariance model); $\Delta$RMSEA = change in RMSEA estimate from less restricted to more restricted model. The partial metric invariance model is compared to the configural invariance model. The strong, strict, factor variance/covariance, and factor mean invariance models are more restrictive models than the partial metric invariance model. * p < .05.
<table>
<thead>
<tr>
<th></th>
<th>$\chi^2$</th>
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<th>#fp</th>
<th>CFI</th>
<th>RMSEA</th>
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<th>$\Delta\chi^2 df$</th>
<th>$\Delta$CFI</th>
<th>$\Delta$RMSEA</th>
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</thead>
<tbody>
<tr>
<td>Configural</td>
<td>16.328</td>
<td>1.119</td>
<td>15</td>
<td>39</td>
<td>.997</td>
<td>.037</td>
<td>(.000 - .125)</td>
<td>-</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Metric</td>
<td>21.286</td>
<td>1.040</td>
<td>19</td>
<td>35</td>
<td>.994</td>
<td>.043</td>
<td>(.000 - .119)</td>
<td>5.201</td>
<td>4</td>
<td>-.002</td>
</tr>
<tr>
<td>Strong</td>
<td>26.287</td>
<td>1.053</td>
<td>23</td>
<td>31</td>
<td>.992</td>
<td>.047</td>
<td>(.000 - .115)</td>
<td>4.972</td>
<td>4</td>
<td>-.003</td>
</tr>
<tr>
<td>Strict</td>
<td>36.552</td>
<td>1.089</td>
<td>29</td>
<td>25</td>
<td>.981</td>
<td>.063</td>
<td>(.000 - .119)</td>
<td>9.883</td>
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<td>-.011</td>
</tr>
<tr>
<td>Factor variance/</td>
<td>38.698</td>
<td>1.072</td>
<td>31</td>
<td>23</td>
<td>.980</td>
<td>.061</td>
<td>(.000 - .116)</td>
<td>2.034</td>
<td>2</td>
<td>.000</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Factor means</td>
<td>48.334*</td>
<td>1.038</td>
<td>33</td>
<td>21</td>
<td>.961</td>
<td>.084</td>
<td>(.017 - .132)</td>
<td>16.958*</td>
<td>2</td>
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</table>

Note. $n = 66$. $\chi^2c =$ scaling correction factor for $\chi^2$; $df =$ degrees of freedom; #fp = number of parameters estimated in each model; CFI = comparative fit index; RMSEA = root mean square error of approximation; $\Delta\chi^2 =$ Satorra-Bentler scaled $\chi^2$ difference statistic; $\Delta\chi^2 df =$ degrees of freedom for Satorra-Bentler $\Delta\chi^2$; $\Delta$CFI = change in CFI estimate from less restricted to more restricted models (i.e., change in CFI from configural invariance model to metric invariance model); $\Delta$RMSEA = change in RMSEA estimate from less restricted to more restricted model. * $p < .05$. 

Table A23

Longitudinal Measurement Invariance Analysis of the WRI’s IR Facet
Table A24

*Longitudinal Measurement Invariance Analysis of the WRI’s SRP-A Facet*

<table>
<thead>
<tr>
<th></th>
<th>$\chi^2$</th>
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<th>$\chi^2 df$</th>
<th>#fp</th>
<th>CFI</th>
<th>RMSEA</th>
<th>$\Delta\chi^2$</th>
<th>$\Delta\chi^2 df$</th>
<th>$\Delta$CFI</th>
<th>$\Delta$RMSEA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Configural</td>
<td>16.677</td>
<td>.886</td>
<td>15</td>
<td>39</td>
<td>.992</td>
<td>.041 (.000 - .127)</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Metric</td>
<td>16.473</td>
<td>.911</td>
<td>19</td>
<td>35</td>
<td>1.000</td>
<td>.000 (.000 - .092)</td>
<td>.227</td>
<td>4</td>
<td>.008</td>
<td>-.041</td>
</tr>
<tr>
<td>Strong</td>
<td>19.742</td>
<td>.908</td>
<td>23</td>
<td>31</td>
<td>1.000</td>
<td>.000 (.000 - .084)</td>
<td>3.266</td>
<td>4</td>
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<td>.000</td>
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<tr>
<td>Strict</td>
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<td>29</td>
<td>25</td>
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<td>.000 (.000 - .058)</td>
<td>3.023</td>
<td>6</td>
<td>.000</td>
<td>.000</td>
</tr>
<tr>
<td>Factor variance/covariance</td>
<td>22.008</td>
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<td>31</td>
<td>23</td>
<td>1.000</td>
<td>.000 (.000 - .046)</td>
<td>.533</td>
<td>2</td>
<td>.000</td>
<td>.000</td>
</tr>
<tr>
<td>Factor means</td>
<td>34.667</td>
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<td>33</td>
<td>21</td>
<td>.992</td>
<td>.028 (.000 - .096)</td>
<td>16.515*</td>
<td>2</td>
<td>-.008</td>
<td>.028</td>
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</tbody>
</table>

*Note. n = 66. $\chi^2c$ = scaling correction factor for $\chi^2$; $df$ = degrees of freedom; #fp = number of parameters estimated in each model; CFI = comparative fit index; RMSEA = root mean square error of approximation; $\Delta\chi^2$ = Satorra-Bentler scaled $\chi^2$ difference statistic; $\Delta\chi^2 df$ = degrees of freedom for Satorra-Bentler $\Delta\chi^2$; $\Delta$CFI = change in CFI estimate from less restricted to more restricted models (i.e., change in CFI from configural invariance model to metric invariance model); $\Delta$RMSEA = change in RMSEA estimate from less restricted to more restricted model. * $p < .05.$*
Table A25

<table>
<thead>
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<th>Level</th>
<th>$\chi^2$</th>
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<th>$\chi^2 df$</th>
<th>#fp</th>
<th>CFI</th>
<th>RMSEA</th>
<th>$\Delta\chi^2$</th>
<th>$\Delta\chi^2 df$</th>
<th>$\Delta$CFI</th>
<th>$\Delta$RMSEA</th>
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<tbody>
<tr>
<td>Configural</td>
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<td>39</td>
<td>.909</td>
<td>.159 (.101 - .220)</td>
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<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Metric</td>
<td>46.941*</td>
<td>.896</td>
<td>19</td>
<td>35</td>
<td>.898</td>
<td>.149 (.096 - .204)</td>
<td>7.549</td>
<td>4</td>
<td>.010</td>
<td>-.010</td>
</tr>
<tr>
<td>Strong</td>
<td>50.272*</td>
<td>.907</td>
<td>23</td>
<td>31</td>
<td>.901</td>
<td>.134 (.083 - .185)</td>
<td>3.666</td>
<td>4</td>
<td>-.002</td>
<td>-.015</td>
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<tr>
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<td>25</td>
<td>.870</td>
<td>.137 (.092 - .182)</td>
<td>14.325*</td>
<td>6</td>
<td>.031</td>
<td>.003</td>
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<tr>
<td>Partial Strict</td>
<td>48.539*</td>
<td>.985</td>
<td>28</td>
<td>26</td>
<td>.925</td>
<td>.105 (.052 - .154)</td>
<td>1.649</td>
<td>5</td>
<td>-.025</td>
<td>-.029</td>
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<td>Factor variance/</td>
<td>48.787*</td>
<td>.994</td>
<td>30</td>
<td>24</td>
<td>.932</td>
<td>.097 (.042 - .146)</td>
<td>.614</td>
<td>2</td>
<td>-.006</td>
<td>-.008</td>
</tr>
<tr>
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<td>50.333*</td>
<td>.989</td>
<td>32</td>
<td>22</td>
<td>.933</td>
<td>.093 (.037 - .140)</td>
<td>1.424</td>
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<td>-.002</td>
<td>-.004</td>
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Note. $n = 66$. $\chi^2_c =$ scaling correction factor for $\chi^2$; $df =$ degrees of freedom; #fp = number of parameters estimated in each model; CFI = comparative fit index; RMSEA = root mean square error of approximation; $\Delta\chi^2 =$ Satorra-Bentler scaled $\chi^2$ difference statistic; $\Delta\chi^2 df =$ degrees of freedom for Satorra-Bentler $\Delta\chi^2$; $\Delta$CFI = change in CFI estimate from less restricted to more restricted models (i.e., change in CFI from configural invariance model to metric invariance model); $\Delta$RMSEA = change in RMSEA estimate from less restricted to more restricted model. * $p < .05$. 

Longitudinal Measurement Invariance Analysis of the WRI’s SRP-B Facet
### Table A26

**Longitudinal Measurement Invariance Analysis of the WRI’s SRP-C Facet**

<table>
<thead>
<tr>
<th></th>
<th>$\chi^2$</th>
<th>$\chi^2_c$</th>
<th>$\chi^2 df$</th>
<th>#fp</th>
<th>CFI</th>
<th>RMSEA</th>
<th>$\Delta\chi^2$</th>
<th>$\Delta\chi^2 df$</th>
<th>$\Delta$CFI</th>
<th>$\Delta$RMSEA</th>
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<tr>
<td>Configural</td>
<td>11.837</td>
<td>1.209</td>
<td>15</td>
<td>39</td>
<td>1.000</td>
<td>.000 (.000 - .092)</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Metric</td>
<td>17.244</td>
<td>1.151</td>
<td>19</td>
<td>35</td>
<td>1.000</td>
<td>.000 (.000 - .097)</td>
<td>5.925</td>
<td>4</td>
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<td>.000</td>
</tr>
<tr>
<td>Strong</td>
<td>21.226</td>
<td>1.136</td>
<td>23</td>
<td>31</td>
<td>1.000</td>
<td>.000 (.000 - .092)</td>
<td>4.005</td>
<td>4</td>
<td>.000</td>
<td>.000</td>
</tr>
<tr>
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<td>29</td>
<td>25</td>
<td>.989</td>
<td>.038 (.000 - .104)</td>
<td>13.206*</td>
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<td>.011</td>
<td>.038</td>
</tr>
<tr>
<td>Partial Strict</td>
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<td>28</td>
<td>26</td>
<td>1.000</td>
<td>.000 (.000 - .082)</td>
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<td>5</td>
<td>.000</td>
<td>.000</td>
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<tr>
<td>Factor variance/ covariance</td>
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<td>30</td>
<td>24</td>
<td>1.000</td>
<td>.000 (.000 - .074)</td>
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<tr>
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<td>9.866</td>
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<td>.006</td>
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</table>

*Note. n = 66. $\chi^2_c = \text{scaling correction factor for } \chi^2$; $df = \text{degrees of freedom}$; #fp = number of parameters estimated in each model; CFI = comparative fit index; RMSEA = root mean square error of approximation; $\Delta\chi^2 = \text{Satorra-Bentler scaled } \chi^2$ difference statistic; $\Delta\chi^2 df = \text{degrees of freedom for Satorra-Bentler } \Delta\chi^2$; $\Delta$CFI = change in CFI estimate from less restricted to more restricted models (i.e., change in CFI from configural invariance model to metric invariance model); $\Delta$RMSEA = change in RMSEA estimate from less restricted to more restricted model. The partial strict invariance model is compared to the strong invariance model. The factor variance/covariance and factor mean invariance models are more restrictive models than the partial strict invariance model. * $p < .05$.*
Table A27

Longitudinal Measurement Invariance Analysis of PsyCap

<table>
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<th>#fp</th>
<th>CFI</th>
<th>RMSEA</th>
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<th>$\Delta\chi^2 df$</th>
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<tr>
<td>Configural</td>
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<td>39</td>
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<td>45</td>
<td>.969</td>
<td>.059 (.000-.106)</td>
<td>4.527</td>
<td>6</td>
<td>.005</td>
<td>-.008</td>
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<tr>
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<td>.940</td>
<td>51</td>
<td>39</td>
<td>.963</td>
<td>.059 (.000-.104)</td>
<td>7.637</td>
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<td>-.005</td>
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<td>59</td>
<td>31</td>
<td>.927</td>
<td>.078 (.031-.115)</td>
<td>21.212*</td>
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<td>-.037</td>
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<td>76.024</td>
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<td>32</td>
<td>.945</td>
<td>.069 (.000-.108)</td>
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<td>-.019</td>
<td>.010</td>
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<tr>
<td>Factor variance/</td>
<td>80.144*</td>
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<td>60</td>
<td>30</td>
<td>.938</td>
<td>.071 (.014-.110)</td>
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<td>-.007</td>
<td>.002</td>
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<td>.931</td>
<td>.074 (.023-.111)</td>
<td>4.056</td>
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<td>-.007</td>
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Note. $n = 66$. $\chi^2_c =$ scaling correction factor for $\chi^2$; $df =$ degrees of freedom; #fp = number of parameters estimated in each model; CFI = comparative fit index; RMSEA = root mean square error of approximation; $\Delta\chi^2 =$ Satorra-Bentler scaled $\chi^2$ difference statistic; $\Delta\chi^2 df =$ degrees of freedom for Satorra-Bentler $\Delta\chi^2$; $\Delta$CFI = change in CFI estimate from less restricted to more restricted models (i.e., change in CFI from configural invariance model to metric invariance model); $\Delta$RMSEA = change in RMSEA estimate from less restricted to more restricted model. The partial strict invariance model is compared to the strong invariance model. The factor variance/covariance and factor mean invariance models are more restrictive models than the partial strict invariance model. * $p < .05$. 

RESILIENCY AND WELL-BEING
Table A28

Longitudinal Measurement Invariance Analysis of PWB

<table>
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<th>Model</th>
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<th>$\chi^2 df$</th>
<th>#fp</th>
<th>CFI</th>
<th>RMSEA</th>
<th>$\Delta \chi^2$</th>
<th>$\Delta \chi^2 df$</th>
<th>$\Delta$CFI</th>
<th>$\Delta$RMSEA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Configural</td>
<td>27.469*</td>
<td>.899</td>
<td>15</td>
<td>39</td>
<td>.967</td>
<td>.112</td>
<td>.039 - .178</td>
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<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Metric</td>
<td>33.207*</td>
<td>.928</td>
<td>19</td>
<td>35</td>
<td>.962</td>
<td>.106</td>
<td>.040 - .165</td>
<td>5.908</td>
<td>4</td>
<td>-.005</td>
</tr>
<tr>
<td>Strong</td>
<td>35.111</td>
<td>.972</td>
<td>23</td>
<td>31</td>
<td>.968</td>
<td>.089</td>
<td>.000 - .146</td>
<td>2.796</td>
<td>4</td>
<td>.006</td>
</tr>
<tr>
<td>Strict</td>
<td>49.938*</td>
<td>.967</td>
<td>29</td>
<td>25</td>
<td>.944</td>
<td>.105</td>
<td>.052 - .153</td>
<td>14.932*</td>
<td>6</td>
<td>-.024</td>
</tr>
<tr>
<td>Factor variance/</td>
<td>43.356</td>
<td>.934</td>
<td>30</td>
<td>24</td>
<td>.964</td>
<td>.082</td>
<td>.000 - .133</td>
<td>.554</td>
<td>2</td>
<td>.001</td>
</tr>
<tr>
<td>covariances</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Factor means</td>
<td>49.869*</td>
<td>.924</td>
<td>32</td>
<td>22</td>
<td>.952</td>
<td>.092</td>
<td>.035 - .139</td>
<td>7.207*</td>
<td>2</td>
<td>-.012</td>
</tr>
</tbody>
</table>

Note. $n = 66$. $\chi^2_c$ = scaling correction factor for $\chi^2$; $df$ = degrees of freedom; #fp = number of parameters estimated in each model; CFI = comparative fit index; RMSEA = root mean square error of approximation; $\Delta \chi^2$ = Satorra-Bentler scaled $\chi^2$ difference statistic; $\Delta \chi^2 df$ = degrees of freedom for Satorra-Bentler $\Delta \chi^2$; $\Delta$CFI = change in CFI estimate from less restricted to more restricted models (i.e., change in CFI from configural invariance model to metric invariance model); $\Delta$RMSEA = change in RMSEA estimate from less restricted to more restricted model. The partial strict invariance model is compared to the strong invariance model. The factor variance/covariance and factor mean invariance models are more restrictive models than the partial strict invariance model. * $p < .05$. 
Table A29

**Longitudinal Measurement Invariance Analysis of JSSE**

<table>
<thead>
<tr>
<th></th>
<th>$\chi^2$</th>
<th>$\chi^2c$</th>
<th>$\chi^2$ df</th>
<th>#fp</th>
<th>CFI</th>
<th>RMSEA</th>
<th>$\Delta\chi^2$</th>
<th>$\Delta\chi^2$ df</th>
<th>$\Delta$CFI</th>
<th>$\Delta$RMSEA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Configural</td>
<td>30.084*</td>
<td>.799</td>
<td>15</td>
<td>39</td>
<td>.961</td>
<td>.123</td>
<td>(.057 -.187)</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Metric</td>
<td>33.385*</td>
<td>.883</td>
<td>19</td>
<td>35</td>
<td>.963</td>
<td>.107</td>
<td>(.041 -.166)</td>
<td>4.542</td>
<td>4</td>
<td>.002 -.016</td>
</tr>
<tr>
<td>Strong</td>
<td>38.818*</td>
<td>.852</td>
<td>23</td>
<td>31</td>
<td>.959</td>
<td>.102</td>
<td>(.040 -.156)</td>
<td>5.104</td>
<td>4</td>
<td>-.004 -.005</td>
</tr>
<tr>
<td>Strict</td>
<td>39.477</td>
<td>.908</td>
<td>29</td>
<td>25</td>
<td>.973</td>
<td>.074</td>
<td>(.000 -.127)</td>
<td>2.464</td>
<td>6</td>
<td>.014 -.028</td>
</tr>
<tr>
<td>Factor variance/</td>
<td>38.146</td>
<td>.943</td>
<td>31</td>
<td>23</td>
<td>.981</td>
<td>.059</td>
<td>(.000 -.115)</td>
<td>.077</td>
<td>2</td>
<td>.009 -.015</td>
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<tr>
<td>covariance</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Factor means</td>
<td>42.113</td>
<td>.951</td>
<td>33</td>
<td>21</td>
<td>.976</td>
<td>.065</td>
<td>(.000 -.117)</td>
<td>3.784</td>
<td>2</td>
<td>-.005 .006</td>
</tr>
</tbody>
</table>

*Note. n = 66. $\chi^2c$ = scaling correction factor for $\chi^2$; df = degrees of freedom; #fp = number of parameters estimated in each model; CFI = comparative fit index; RMSEA = root mean square error of approximation; $\Delta\chi^2$ = Satorra-Bentler scaled $\chi^2$ difference statistic; $\Delta\chi^2$ df = degrees of freedom for Satorra-Bentler $\Delta\chi^2$; $\Delta$CFI = change in CFI estimate from less restricted to more restricted models (i.e., change in CFI from configural invariance model to metric invariance model); $\Delta$RMSEA = change in RMSEA estimate from less restricted to more restricted model. * $p < .05.$
Appendix T – Study 2 Sensitivity Analyses, Hierarchical Multiple Regression

Table A30

Hierarchical Multiple Regression Results for Time 1 → Time 2 PWB on Time 1 → Time 2 WRI and PsyCap Predictors, Reduced Sample

<table>
<thead>
<tr>
<th></th>
<th>Step 1 Bs</th>
<th>Step 2 Bs</th>
</tr>
</thead>
<tbody>
<tr>
<td>PC-A</td>
<td>-.153</td>
<td>-.152</td>
</tr>
<tr>
<td>PC-B</td>
<td>.295*</td>
<td>.324**</td>
</tr>
<tr>
<td>PC-C</td>
<td>-.225</td>
<td>-.192</td>
</tr>
<tr>
<td>IR</td>
<td>-.131</td>
<td>-.154</td>
</tr>
<tr>
<td>OSR</td>
<td>-.320**</td>
<td>-.290*</td>
</tr>
<tr>
<td>SRP-A</td>
<td>-.036</td>
<td>-.017</td>
</tr>
<tr>
<td>SRP-B</td>
<td>.009</td>
<td>-.034</td>
</tr>
<tr>
<td>SRP-C</td>
<td>.184</td>
<td>.232</td>
</tr>
<tr>
<td>PsyCap</td>
<td></td>
<td>-.186</td>
</tr>
</tbody>
</table>

\[ R^2 \quad .341** (.249) \quad .368** (.266) \]

\[ \Delta R^2 \quad .026 (.017) \]

Note. \( n = 66 \). Values in parentheses are adjusted \( R^2 \) estimates. Table presents standardized regression coefficients. * \( p < .05 \), ** \( p < .01 \).
Table A31

*Hierarchical Multiple Regression Results for Time 2 → Time 3 PWB on Time 1 → Time 2 WRI and PsyCap Predictors, Reduced Sample*

<table>
<thead>
<tr>
<th></th>
<th>Step 1 Bs</th>
<th>Step 2 Bs</th>
</tr>
</thead>
<tbody>
<tr>
<td>PC-A</td>
<td>.277*</td>
<td>.277*</td>
</tr>
<tr>
<td>PC-B</td>
<td>-.134</td>
<td>-.130</td>
</tr>
<tr>
<td>PC-C</td>
<td>-.087</td>
<td>-.083</td>
</tr>
<tr>
<td>IR</td>
<td>.256</td>
<td>.253</td>
</tr>
<tr>
<td>OSR</td>
<td>.005</td>
<td>.009</td>
</tr>
<tr>
<td>SRP-A</td>
<td>-.039</td>
<td>-.037</td>
</tr>
<tr>
<td>SRP-B</td>
<td>.298*</td>
<td>.293*</td>
</tr>
<tr>
<td>SRP-C</td>
<td>.251</td>
<td>.257</td>
</tr>
<tr>
<td>PsyCap</td>
<td></td>
<td>-.025</td>
</tr>
</tbody>
</table>

\[
R^2 \quad .211 (.100) \quad .211^* (.084)
\]

\[
\Delta R^2 \quad .000 (-.016)
\]

*Note. n = 66. Values in parentheses are adjusted R² estimates. Table presents standardized regression coefficients. * p < .05, ** p < .01.*
Table A32

*Hierarchical Multiple Regression Results for Time 2 → Time 3 PWB on Time 2 → Time 3 WRI and PsyCap Predictors, Reduced Sample*

<table>
<thead>
<tr>
<th></th>
<th>Step 1 Bs</th>
<th>Step 2 Bs</th>
</tr>
</thead>
<tbody>
<tr>
<td>PC-A</td>
<td>-.425**</td>
<td>-.361**</td>
</tr>
<tr>
<td>PC-B</td>
<td>.038</td>
<td>.017</td>
</tr>
<tr>
<td>PC-C</td>
<td>.062</td>
<td>.055</td>
</tr>
<tr>
<td>IR</td>
<td>-.415**</td>
<td>-.383**</td>
</tr>
<tr>
<td>OSR</td>
<td>-.091</td>
<td>-.075</td>
</tr>
<tr>
<td>SRP-A</td>
<td>.031</td>
<td>-.047</td>
</tr>
<tr>
<td>SRP-B</td>
<td>-.362**</td>
<td>-.283*</td>
</tr>
<tr>
<td>SRP-C</td>
<td>.046</td>
<td>-.010</td>
</tr>
<tr>
<td>PsyCap</td>
<td></td>
<td>.230*</td>
</tr>
</tbody>
</table>

\[ R^2 \] .458** (.382) \quad .495** (.413)  
\[ \Delta R^2 \] .037* (.031)

*Note. n = 66. Values in parentheses are adjusted R\(^2\) estimates. Table presents standardized regression coefficients. * p < .05, ** p < .01.*
Table A33

*Hierarchical Multiple Regression Results for Time 1 → Time 2 JSSE on Time 1 → Time 2 WRI and PsyCap Predictors, Reduced Sample*

<table>
<thead>
<tr>
<th></th>
<th>Step 1 Bs</th>
<th>Step 2 Bs</th>
</tr>
</thead>
<tbody>
<tr>
<td>PC-A</td>
<td>-.084</td>
<td>-.085</td>
</tr>
<tr>
<td>PC-B</td>
<td>.292*</td>
<td>.282*</td>
</tr>
<tr>
<td>PC-C</td>
<td>.116</td>
<td>.104</td>
</tr>
<tr>
<td>IR</td>
<td>-.097</td>
<td>-.089</td>
</tr>
<tr>
<td>OSR</td>
<td>-.062</td>
<td>-.073</td>
</tr>
<tr>
<td>SRP-A</td>
<td>-.001</td>
<td>-.008</td>
</tr>
<tr>
<td>SRP-B</td>
<td>.141</td>
<td>.156</td>
</tr>
<tr>
<td>SRP-C</td>
<td>.052</td>
<td>.035</td>
</tr>
<tr>
<td>PsyCap</td>
<td></td>
<td>.066</td>
</tr>
</tbody>
</table>

\[
R^2 = .197 (.084) \quad \text{and} \quad .200 (-.013)
\]
\[
\Delta R^2 = .003 (.002)
\]

*Note. n = 66. Values in parentheses are adjusted $R^2$ estimates. Table presents standardized regression coefficients. * $p < .05$, ** $p < .01$.\]
### Table A34

*Hierarchical Multiple Regression Results for Time 2 → Time 3 JSSE on Time 1 → Time 2 WRI and PsyCap Predictors, Reduced Sample*

<table>
<thead>
<tr>
<th></th>
<th>Step 1 Bs</th>
<th>Step 2 Bs</th>
</tr>
</thead>
<tbody>
<tr>
<td>PC-A</td>
<td>.136</td>
<td>.137</td>
</tr>
<tr>
<td>PC-B</td>
<td>-.052</td>
<td>-.041</td>
</tr>
<tr>
<td>PC-C</td>
<td>.036</td>
<td>.048</td>
</tr>
<tr>
<td>IR</td>
<td>.012</td>
<td>.003</td>
</tr>
<tr>
<td>OSR</td>
<td>.075</td>
<td>.086</td>
</tr>
<tr>
<td>SRP-A</td>
<td>-.078</td>
<td>-.071</td>
</tr>
<tr>
<td>SRP-B</td>
<td>-.146</td>
<td>-.162</td>
</tr>
<tr>
<td>SRP-C</td>
<td>.200</td>
<td>.218</td>
</tr>
<tr>
<td>PsyCap</td>
<td></td>
<td>-.071</td>
</tr>
</tbody>
</table>

\[
R^2 \quad .067 (-.064) \quad .071 (-.078) \\
\Delta R^2 \quad .004 (-.014)
\]

*Note. n = 66. Values in parentheses are adjusted \( R^2 \) estimates. Table presents standardized regression coefficients. * \( p < .05 \), ** \( p < .01 \).*
Table A35

Hierarchical Multiple Regression Results for Time 2 → Time 3 JSSE on Time 2 → Time 3 WRI and PsyCap Predictors, Reduced Sample

<table>
<thead>
<tr>
<th></th>
<th>Step 1 Bs</th>
<th>Step 2 Bs</th>
</tr>
</thead>
<tbody>
<tr>
<td>PC-A</td>
<td>-.142</td>
<td>-.108</td>
</tr>
<tr>
<td>PC-B</td>
<td>.141</td>
<td>.130</td>
</tr>
<tr>
<td>PC-C</td>
<td>.025</td>
<td>.022</td>
</tr>
<tr>
<td>IR</td>
<td>-.152</td>
<td>-.135</td>
</tr>
<tr>
<td>OSR</td>
<td>-.277*</td>
<td>-.269*</td>
</tr>
<tr>
<td>SRP-A</td>
<td>.181</td>
<td>.140</td>
</tr>
<tr>
<td>SRP-B</td>
<td>-.056</td>
<td>-.014</td>
</tr>
<tr>
<td>SRP-C</td>
<td>.146</td>
<td>.116</td>
</tr>
<tr>
<td>PsyCap</td>
<td></td>
<td>.123</td>
</tr>
</tbody>
</table>

\[
R^2 \quad .197 (.084) \quad .207 (.080) \\
\Delta R^2 \quad .011 (-.004)
\]

Note. \( n = 66 \). Values in parentheses are adjusted \( R^2 \) estimates. Table presents standardized regression coefficients. * \( p < .05 \), ** \( p < .01 \).
Appendix U – Study 2 Drop-out Effects

Table A36

*Logistic Regression: Stayers versus Leavers*

<table>
<thead>
<tr>
<th></th>
<th>$b$</th>
<th>$SE$</th>
<th>OR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-.152</td>
<td>6.845</td>
<td>.859</td>
</tr>
<tr>
<td>Sex</td>
<td>-.113</td>
<td>.698</td>
<td>.893</td>
</tr>
<tr>
<td>Age</td>
<td>-.050</td>
<td>.051</td>
<td>.951</td>
</tr>
<tr>
<td>Education</td>
<td>-.445**</td>
<td>.165</td>
<td>.641</td>
</tr>
<tr>
<td>Organizational level</td>
<td>1.140</td>
<td>.650</td>
<td>3.128</td>
</tr>
<tr>
<td>Functional area</td>
<td>-.027</td>
<td>.129</td>
<td>.973</td>
</tr>
<tr>
<td>Tenure</td>
<td>.000</td>
<td>.009</td>
<td>1.000</td>
</tr>
<tr>
<td>PC-A</td>
<td>-.753</td>
<td>.678</td>
<td>.471</td>
</tr>
<tr>
<td>PC-B</td>
<td>-.169</td>
<td>1.009</td>
<td>.844</td>
</tr>
<tr>
<td>PC-C</td>
<td>.856</td>
<td>.662</td>
<td>2.353</td>
</tr>
<tr>
<td>OSR</td>
<td>-1.298**</td>
<td>.499</td>
<td>.273</td>
</tr>
<tr>
<td>IR</td>
<td>.162</td>
<td>.474</td>
<td>1.176</td>
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<tr>
<td>SRP-A</td>
<td>1.189</td>
<td>.700</td>
<td>3.285</td>
</tr>
<tr>
<td>SRP-B</td>
<td>-1.110</td>
<td>.834</td>
<td>.330</td>
</tr>
<tr>
<td>SRP-C</td>
<td>.183</td>
<td>.780</td>
<td>1.201</td>
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<tr>
<td>PsyCap</td>
<td>2.188</td>
<td>1.609</td>
<td>8.914</td>
</tr>
<tr>
<td>PWB</td>
<td>-1.026</td>
<td>1.313</td>
<td>.359</td>
</tr>
<tr>
<td>JSSE</td>
<td>-.040</td>
<td>.626</td>
<td>.961</td>
</tr>
</tbody>
</table>

Nagelkerke $R^2$       | .430|
Cox & Snell $R^2$      | .305|
$-2LL$                 | 76.096|
$\chi^2$ (df)          | 31.676* (17)

*Note. OR = odds ratios. * $p < .05$, ** $p < .01$. 
Table A37

*T-tests: Stayers versus Leavers*

<table>
<thead>
<tr>
<th>Variable</th>
<th>Stayer</th>
<th>Leaver</th>
<th>t(109)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sex</td>
<td>1.406 (.499)</td>
<td>1.481 (.503)</td>
<td>.704</td>
</tr>
<tr>
<td>Age</td>
<td>52.226 (8.413)</td>
<td>53.414 (7.031)</td>
<td>.737</td>
</tr>
<tr>
<td>Education</td>
<td>5.563 (2.199)</td>
<td>5.923 (2.266)</td>
<td>.764</td>
</tr>
<tr>
<td>Organization level</td>
<td>3.594 (.875)</td>
<td>3.154 (1.14)</td>
<td>-1.957</td>
</tr>
<tr>
<td>Functional area</td>
<td>3.125 (2.791)</td>
<td>2.872 (2.669)</td>
<td>-.446</td>
</tr>
<tr>
<td>Tenure</td>
<td>41.839 (36.046)</td>
<td>43.881 (43.931)</td>
<td>.230</td>
</tr>
<tr>
<td>PC-A</td>
<td>3.692 (.573)</td>
<td>3.783 (.651)</td>
<td>.679</td>
</tr>
<tr>
<td>PC-B</td>
<td>4.428 (.447)</td>
<td>4.388 (.468)</td>
<td>-.408</td>
</tr>
<tr>
<td>PC-C</td>
<td>4.024 (.511)</td>
<td>3.843 (.630)</td>
<td>-1.423</td>
</tr>
<tr>
<td>OSR</td>
<td>4.008 (.991)</td>
<td>4.315 (.709)</td>
<td>1.814</td>
</tr>
<tr>
<td>IR</td>
<td>2.478 (.833)</td>
<td>2.476 (.881)</td>
<td>-.014</td>
</tr>
<tr>
<td>SRP-A</td>
<td>3.761 (.555)</td>
<td>3.645 (.609)</td>
<td>-.921</td>
</tr>
<tr>
<td>SRP-B</td>
<td>3.495 (.559)</td>
<td>3.572 (.524)</td>
<td>.678</td>
</tr>
<tr>
<td>SRP-C</td>
<td>3.666 (.618)</td>
<td>3.521 (.664)</td>
<td>-1.047</td>
</tr>
<tr>
<td>PsyCap</td>
<td>4.112 (.416)</td>
<td>4.040 (.359)</td>
<td>-.880</td>
</tr>
<tr>
<td>PWB</td>
<td>3.744 (.434)</td>
<td>3.783 (.355)</td>
<td>.469</td>
</tr>
<tr>
<td>JSSE</td>
<td>3.904 (.687)</td>
<td>3.843 (.646)</td>
<td>-.418</td>
</tr>
</tbody>
</table>

*Note.* Standard deviations in parentheses. *p < .05.*
Table A38

*Differences in Variances: Whole Sample versus Stayers*

<table>
<thead>
<tr>
<th>Variable</th>
<th>Whole Sample</th>
<th>Stayer</th>
<th>z^a</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sex</td>
<td>.251</td>
<td>.249</td>
<td>-.026</td>
</tr>
<tr>
<td>Age</td>
<td>55.648</td>
<td>7.781</td>
<td>1.088</td>
</tr>
<tr>
<td>Education</td>
<td>5.031</td>
<td>4.835</td>
<td>-.156</td>
</tr>
<tr>
<td>Organizational level</td>
<td>1.177</td>
<td>.765</td>
<td>-1.399</td>
</tr>
<tr>
<td>Functional area</td>
<td>7.263</td>
<td>7.790</td>
<td>.290</td>
</tr>
<tr>
<td>Tenure</td>
<td>1739.496</td>
<td>1299.340</td>
<td>-1.012</td>
</tr>
<tr>
<td>PC-A</td>
<td>.395</td>
<td>.328</td>
<td>-.680</td>
</tr>
<tr>
<td>PC-B</td>
<td>.211</td>
<td>.199</td>
<td>-.227</td>
</tr>
<tr>
<td>PC-C</td>
<td>.362</td>
<td>.262</td>
<td>-1.112</td>
</tr>
<tr>
<td>OSR</td>
<td>.651</td>
<td>.983</td>
<td>2.042^*</td>
</tr>
<tr>
<td>IR</td>
<td>.745</td>
<td>.694</td>
<td>-.274</td>
</tr>
<tr>
<td>SRP-A</td>
<td>.352</td>
<td>.308</td>
<td>-.505</td>
</tr>
<tr>
<td>SRP-B</td>
<td>.284</td>
<td>.312</td>
<td>.393</td>
</tr>
<tr>
<td>SRP-C</td>
<td>.424</td>
<td>.383</td>
<td>-.393</td>
</tr>
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<td>PsyCap</td>
<td>.141</td>
<td>.173</td>
<td>.893</td>
</tr>
<tr>
<td>PWB</td>
<td>.143</td>
<td>.188</td>
<td>1.259</td>
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<tr>
<td>JSSE</td>
<td>.430</td>
<td>.472</td>
<td>.391</td>
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</tbody>
</table>

*Note.* n_{Whole Sample} = 111, n_{Stayer} = 33. * p < .05. ^a two-tailed z-test as detailed in Goodman & Blum (1996), critical z = |1.96|.
Table A39

**Results of Regression Analyses: Psychological Well-Being**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Whole Sample</th>
<th>Stayers</th>
<th>( t^a )</th>
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<td>Sex</td>
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<td>.172</td>
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<td>Age</td>
<td>-.005</td>
<td>-.011</td>
<td>.009</td>
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<tr>
<td>Education</td>
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<td>.050</td>
<td>.026</td>
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<tr>
<td>Organizational level</td>
<td>-.035</td>
<td>-.151</td>
<td>.147</td>
</tr>
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<td>Functional area</td>
<td>-.015</td>
<td>.005</td>
<td>.025</td>
</tr>
<tr>
<td>Tenure</td>
<td>.000</td>
<td>.005*</td>
<td>.002</td>
</tr>
<tr>
<td>PC-A</td>
<td>-.006</td>
<td>-.031</td>
<td>.109</td>
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<tr>
<td>PC-B</td>
<td>.080</td>
<td>-.021</td>
<td>.240</td>
</tr>
<tr>
<td>PC-C</td>
<td>.076</td>
<td>-.419*</td>
<td>.154</td>
</tr>
<tr>
<td>OSR</td>
<td>.156*</td>
<td>.016</td>
<td>.070</td>
</tr>
<tr>
<td>IR</td>
<td>.036</td>
<td>.006</td>
<td>.056</td>
</tr>
<tr>
<td>SRP-A</td>
<td>-.108</td>
<td>-.279*</td>
<td>.123</td>
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<tr>
<td>SRP-B</td>
<td>.050</td>
<td>-.039</td>
<td>.163</td>
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<tr>
<td>SRP-C</td>
<td>.098</td>
<td>.357*</td>
<td>.143</td>
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<td>PsyCap</td>
<td>.188</td>
<td>.434</td>
<td>.213</td>
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<tr>
<td>JSSE</td>
<td>.185*</td>
<td>.321</td>
<td>.171</td>
</tr>
</tbody>
</table>

\[ F = 6.082 \quad 8.960 \]
\[ R^2 = .582* \quad .635* \]

Adjusted \( R^2 \) = .486 \quad .530

*Note.* Table presents unstandardized coefficients. \( n_{\text{Whole Sample}} = 111 \), \( n_{\text{Stayer}} = 33 \). * \( p < .05 \). * Two-tailed \( t \)-tests are shown for the difference between coefficients that were found to be significant in the Whole Sample, but not in the Stayers, and vice versa.
Appendix V – Study 2 Longitudinal Confirmatory Factor Analyses

Psychological Well-being. Table A13 documents the results of the MI tests of the PWB measure used in this study. As with the LCFA analyses of the PWB measure conducted in Study 1, the configural invariance model appeared to the data reasonably well, exhibiting $\chi^2(15) = 27.161$, $p = .028$, and CFI and RMSEA estimates of .970 and .089 (90% CI = .029 -.141), respectively. Adding the equality constraints across the PWB’s parcels across all three timepoints resulted in a non-significant $\Delta \chi^2(4) = 8.693$, $p = .069$. Thus, suggesting that the parcel’s factor loadings are equivalent across timepoints. Next, adding the equality constraints across all three timepoints respective parcel means similarly resulted in a non-significant decrease in model-data correspondence, $\Delta \chi^2(4) = 2.759$, $p = .599$. Therefore, the PWB item parcels displayed similar means over time.

Building upon the equality constraints on the means of the PWB parcels in the previous scalar invariance stage, the next step was to add equality constraints over respective parcel residual variances. Imposing all six constraints, in contrast to all of the other invariance analyses conducted so far in Study 1 or 2 resulted in a change in model fit that was unacceptably large. In particular, according to the $\Delta \chi^2$ test model fit of this strict invariance model was significantly worse than that of the scalar invariance model, $\Delta \chi^2(6) = 13.778$, $p = .032$. Thus, it became necessary to investigate the partial MI of the PWB measure by relaxing one the residual variance constraints imposed. I consulted the modification indices and also the residual variance estimates from the scalar invariance model to determine which constraint(s) were likely to be causing this misfit. I determined that a residual variance for one of the item parcels at Time 2 was substantially smaller than at Time 1 or Time 3. Thus, relaxing this equality constraint allowed me to estimate a partial strict invariance model in which all but one of the residual variances was
Table A40

*Longitudinal Measurement Invariance Analysis of PWB*

<table>
<thead>
<tr>
<th>Model Type</th>
<th>$\chi^2$</th>
<th>$\chi^2c$</th>
<th>$\chi^2 df$</th>
<th>#fp</th>
<th>CFI</th>
<th>RMSEA</th>
<th>$\Delta\chi^2$</th>
<th>$\Delta\chi^2 df$</th>
<th>$\Delta$CFI</th>
<th>$\Delta$RMSEA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Configural</td>
<td>27.161*</td>
<td>.914</td>
<td>15</td>
<td>39</td>
<td>.970</td>
<td>.089</td>
<td>(.029 - .141)</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Metric</td>
<td>35.985**</td>
<td>.937</td>
<td>19</td>
<td>35</td>
<td>.958</td>
<td>.093</td>
<td>(.044 - .139)</td>
<td>8.693</td>
<td>4</td>
<td>-.012</td>
</tr>
<tr>
<td>Strong</td>
<td>38.219*</td>
<td>.959</td>
<td>23</td>
<td>31</td>
<td>.962</td>
<td>.080</td>
<td>(.029 - .124)</td>
<td>2.759</td>
<td>4</td>
<td>.004</td>
</tr>
<tr>
<td>Strict</td>
<td>51.999**</td>
<td>.959</td>
<td>29</td>
<td>25</td>
<td>.943</td>
<td>.088</td>
<td>(.047 - .126)</td>
<td>13.778*</td>
<td>6</td>
<td>-.019</td>
</tr>
<tr>
<td>Partial Strict</td>
<td>44.904*</td>
<td>.958</td>
<td>28</td>
<td>26</td>
<td>.958</td>
<td>.077</td>
<td>(.029 - .117)</td>
<td>6.676</td>
<td>5</td>
<td>-.004</td>
</tr>
<tr>
<td>Factor variance/covariance</td>
<td>48.022*</td>
<td>.923</td>
<td>30</td>
<td>24</td>
<td>.955</td>
<td>.076</td>
<td>(.031 - .115)</td>
<td>3.017</td>
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<td>-.003</td>
</tr>
<tr>
<td>Factor means</td>
<td>55.364**</td>
<td>.917</td>
<td>32</td>
<td>22</td>
<td>.942</td>
<td>.084</td>
<td>(.045 - .121)</td>
<td>7.776*</td>
<td>2</td>
<td>-.013</td>
</tr>
</tbody>
</table>

*Note.* $n = 111$. $\chi^2c =$ scaling correction factor for $\chi^2$; $df =$ degrees of freedom; #fp = number of parameters estimated in each model; CFI = comparative fit index; RMSEA = root mean square error of approximation; $\Delta\chi^2 =$ Satorra-Bentler scaled $\chi^2$ difference statistic; $\Delta\chi^2 df =$ degrees of freedom for Satorra-Bentler $\Delta\chi^2$; $\Delta$CFI = change in CFI estimate from less restricted to more restricted models (i.e., change in CFI from configural invariance model to metric invariance model); $\Delta$RMSEA = change in RMSEA estimate from less restricted to more restricted model. The partial strict invariance model is compared to the strong invariance model. The factor variance/covariance and factor mean invariance models are more restrictive models than the partial strict invariance model. * $p < .05$, ** $p < .01$, *** $p < .001$. 
constrained to equality. Particularly, in comparison to the scalar invariance model, this partial strict invariance model demonstrated a $\Delta \chi^2(5) = 6.676$, $p = .246$. Thus, the PWB measure demonstrated partial strict invariance over time.

Although this is not as strong evidence for the longitudinal validity of the PWB measure as that presented by Study 1, methodologists have suggested that additional analyses are still supportable in spite of the lack of invariance, therefore, based on this partial strict invariance model I added the equality constraints on the variance of the PWB latent factor to continue testing the measure’s longitudinal MI. The two equality constraints on the factor variances over the three timepoints resulted in a $\Delta \chi^2(2) = 3.017$, $p = .221$. Thus, the variances of the latent PWB factor were equivalent across timepoints. The last stage of the MI analyses considered whether the latent factor means were equivalent across timepoints. Imposing these two additional constraints led to a significant decrease in model-data fit, $\Delta \chi^2(2) = 7.776$, $p = .020$. This would suggest that the latent PWB means differ significantly over time. In light of this, I referred back to the results of the factor variance invariance model in order to gain insight into the pattern of PWB mean differences over time. Interestingly, the Time 2 estimate was negative, and the Time 3 estimate was positive. As Time 1 was fixed to zero for model identification purposes, this would suggest Time 2 PWB was lower at Time 2 than Time 1, but higher than Time 1 at Time 3. Having said that however, neither of the latent mean estimates were significantly different from zero, $\mu_{\text{Time 2}} = -.118$, $p = .269$, $\mu_{\text{Time 3}} = .220$, $p = .139$. But despite these non-significant deviations from zero, if both Time 2 and Time 3 means were constrained to zero (to make them equal to the Time 1 mean) model fit was significantly worse. Thus, across all three timepoints there appeared to be some evidence of different latent PWB means, albeit in a somewhat curvilinear fashion.
**Job Search Self-Efficacy.** Table A14 documents the results of the longitudinal MI tests of the JSSE measure used. The configural invariance model appeared to the data reasonably well, exhibiting a $\chi^2(15) = 31.131$, $p = .008$, and CFI and RMSEA estimates of .963 and .103, respectively (with a RMSEA 90% CI = .050 - .154). Throughout the metric, scalar, strict, factor variance, or fact means MI tests, none of the equality constraints significantly impacted model-data fit according to the $\Delta \chi^2$ test. Supporting metric invariance was a $\Delta \chi^2(4) = 5.497$, $p = .240$, suggesting that the factor loadings of the item parcels were invariant across timepoints. Supporting scalar invariance was a $\Delta \chi^2(4) = 6.511$, $p = .164$, suggesting that the observed item parcel means were equivalent across timepoints. Supporting strict invariance was a $\Delta \chi^2(6) = 2.206$, $p = .900$, which suggests that the residual variances of the JSSE item parcel were similar across repeated measures. Adding the equality constraints over the JSSE latent factor variances also did not result in a significant decrease in model fit, $\Delta \chi^2(2) = .018$, $p = .991$. Thus, the variances of the latent factor were equivalent across timepoints. Finally, the latent means were also found to be equivalent across the three timepoints assessed, $\Delta \chi^2(2) = 4.253$, $p = .119$. Therefore, the longitudinal validity of the JSSE measure was supported.

**Psychological Capital.** The configural invariance model resulted in an acceptable degree of model-data fit, with a $\chi^2(39) = 56.368$, $p = .036$, CFI = .952, and a RMSEA of .065 (90% CI = .018 - .101). As shown in Table A15, adding the factor loading constraints on the four respective facets over the three measurement occasions did not result in a significant decrease in model-data fit, $\Delta \chi^2(6) = 4.446$, $p = .616$. Thus, the loadings of the single PsyCap latent variable on the four facets were equivalent across timepoints. Next, adding the equality constraints on the facet intercepts was also not found to significant alter model fit, $\Delta \chi^2(6) = 9.378$, $p = .153$. This
Table A41

Longitudinal Measurement Invariance Analysis of JSSE

<table>
<thead>
<tr>
<th></th>
<th>$\chi^2$</th>
<th>$\chi^2_c$</th>
<th>$\chi^2_{df}$</th>
<th>#fp</th>
<th>CFI</th>
<th>RMSEA</th>
<th>$\Delta\chi^2$</th>
<th>$\Delta\chi^2_{df}$</th>
<th>$\Delta$CFI</th>
<th>$\Delta$RMSEA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Configural</td>
<td>31.131**</td>
<td>.784</td>
<td>15</td>
<td>39</td>
<td>.963</td>
<td>.103 (.050 - .154)</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Metric</td>
<td>35.800*</td>
<td>.851</td>
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<td>35</td>
<td>.962</td>
<td>.093 (.044 - .139)</td>
<td>5.497</td>
<td>4</td>
<td>-.002</td>
<td>-.010</td>
</tr>
<tr>
<td>Strong</td>
<td>42.449**</td>
<td>.827</td>
<td>23</td>
<td>31</td>
<td>.956</td>
<td>.091 (.046 - .133)</td>
<td>6.511</td>
<td>4</td>
<td>-.006</td>
<td>-.002</td>
</tr>
<tr>
<td>Strict</td>
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<td>.905</td>
<td>29</td>
<td>25</td>
<td>.971</td>
<td>.066 (.000 - .107)</td>
<td>2.206</td>
<td>6</td>
<td>.015</td>
<td>-.025</td>
</tr>
<tr>
<td>Factor variance/covariance</td>
<td>39.987</td>
<td>.945</td>
<td>31</td>
<td>23</td>
<td>.979</td>
<td>.053 (.000 - .096)</td>
<td>.018</td>
<td>2</td>
<td>.009</td>
<td>-.013</td>
</tr>
<tr>
<td>Factor means</td>
<td>44.463</td>
<td>.953</td>
<td>33</td>
<td>21</td>
<td>.974</td>
<td>.058 (.000 - .099)</td>
<td>4.253</td>
<td>2</td>
<td>-.006</td>
<td>.005</td>
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</table>

Note. $n = 111$. $\chi^2_c$ = scaling correction factor for $\chi^2$; $df$ = degrees of freedom; #fp = number of parameters estimated in each model; CFI = comparative fit index; RMSEA = root mean square error of approximation; $\Delta\chi^2 = $ Satorra-Bentler scaled $\chi^2$ difference statistic; $\Delta\chi^2_{df} = $ degrees of freedom for Satorra-Bentler $\Delta\chi^2$; $\Delta$CFI = change in CFI estimate from less restricted to more restricted models (i.e., change in CFI from configural invariance model to metric invariance model); $\Delta$RMSEA = change in RMSEA estimate from less restricted to more restricted model. * $p < .05$, ** $p < .01$, *** $p < .001$. 
Table A42

Longitudinal Measurement Invariance Analysis of PsyCap

<table>
<thead>
<tr>
<th>Model</th>
<th>$\chi^2$</th>
<th>$\chi^2_c$</th>
<th>$\chi^2_{df}$</th>
<th>#fp</th>
<th>CFI</th>
<th>RMSEA</th>
<th>$\Delta\chi^2$</th>
<th>$\Delta\chi^2_{df}$</th>
<th>$\Delta$CFI</th>
<th>$\Delta$RMSEA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Configural</td>
<td>56.368*</td>
<td>.896</td>
<td>39</td>
<td>51</td>
<td>.952</td>
<td>.065 (.018 -.101)</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Metric</td>
<td>60.741</td>
<td>.898</td>
<td>45</td>
<td>45</td>
<td>.957</td>
<td>.058 (.000 -.092)</td>
<td>4.446</td>
<td>6</td>
<td>.004</td>
<td>-.007</td>
</tr>
<tr>
<td>Strong</td>
<td>70.449*</td>
<td>.930</td>
<td>51</td>
<td>39</td>
<td>.947</td>
<td>.060 (.016 -.092)</td>
<td>9.378</td>
<td>6</td>
<td>-.010</td>
<td>.002</td>
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<tr>
<td>Strict</td>
<td>86.689*</td>
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<td>59</td>
<td>31</td>
<td>.924</td>
<td>.067 (.033 -.096)</td>
<td>16.476*</td>
<td>8</td>
<td>-.023</td>
<td>.007</td>
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<tr>
<td>Partial Strict</td>
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<td>32</td>
<td>.938</td>
<td>.061 (.021 -.091)</td>
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<td>-.008</td>
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<td>30</td>
<td>.933</td>
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<td>.001</td>
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<tr>
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<td>62</td>
<td>28</td>
<td>.927</td>
<td>.064 (.029 -.092)</td>
<td>4.025</td>
<td>2</td>
<td>-.006</td>
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</tbody>
</table>

Note. $n = 111$. $\chi^2_c$ = scaling correction factor for $\chi^2$; $df$ = degrees of freedom; #fp = number of parameters estimated in each model; CFI = comparative fit index; RMSEA = root mean square error of approximation; $\Delta\chi^2 = $ Satorra-Bentler scaled $\chi^2$ difference statistic; $\Delta\chi^2_{df} = $ degrees of freedom for Satorra-Bentler $\Delta\chi^2$; $\Delta$CFI = change in CFI estimate from less restricted to more restricted models (i.e., change in CFI from configural invariance model to metric invariance model); $\Delta$RMSEA = change in RMSEA estimate from less restricted to more restricted model. The partial strict invariance model is compared to the strong invariance model. The factor variance/covariance and factor mean invariance models are more restrictive models than the partial strict invariance model. * $p < .05$, ** $p < .01$, *** $p < .001$. 
suggests that the means of the respective PsyCap facets were equal across the three measurement periods.

As in the PWB measure, adding the equality constraints on the residual variances in the strict invariance stage resulted in a significant decrease in model fit, $\Delta \chi^2(8) = 16.476$, $p = .036$. Thus, it was necessary to investigate partial invariance of the residual variances of the PsyCap facets as well. In this case, through investigating the modification indices and the residual variance estimates from the scalar invariance model I found that the Time 3 Self-Efficacy facet had lower variance than the Time 1 and Time 2 assessments. Thus, in pursuit of a partially invariant strict invariance model, I freed the equality constraint previously applied to the Time 3 Self-Efficacy measure. In comparison to the scalar invariance model, this partial strict invariance model did not suggest a significant decrease in model fit, $\Delta \chi^2(7) = 9.957$, $p = .191$. Thus, the variance of the Self-Efficacy facet was found to vary, and get smaller, in Time 3 as compared to the Time 1 and Time 2 assessments. This, then leads to an overall assessment of partial invariance over time.

Continuing with the PsyCap’s longitudinal MI analyses, despite the evidence of partial strict invariance, I next applied equality constraints over the latent PsyCap variances. This step was found not to significantly reduce model-data fit, $\Delta \chi^2(2) = 4.465$, $p = .107$, suggesting that, after allowing for an unequal Time 3 Self-Efficacy variance, the variances of the latent (higher-order) factors are equivalent over timepoints. Lastly, I applied equality constraints over the latent PsyCap means. Equality of latent PsyCap means was supported in that a non-significant $\Delta \chi^2$ estimate resulted, test $\Delta \chi^2(2) = 4.025$, $p = .134$.

Thus, the PsyCap measure demonstrated evidence of longitudinal validity, and despite its partial strict invariance warrants use in further longitudinal analyses.
**Workplace Resiliency Inventory.** The longitudinal MI analyses on the WRI were also conducted slightly differently in Study 2 than Study 1. I approached these MI analyses in a scale-by-scale manner in light of the more modest sample size in Study 2. Thus, rather than examine the MI of the entire WRI over three timepoints it was necessary to examine the invariant properties of each facet scale independently. Examining the MI of the WRI in the same manner as Study 1 would have likely led to model convergence issues and biased parameter estimates. In order to avoid these issues, I took a more narrowly focused perspective on the MI of the WRI for Study 2.

The pattern of MI results is quite similar for many of the WRI facets, so I report the change in model fit in broad terms only; full details are available in Tables A16-A23. For the PC-A, PC-B, IR, SRP-A, and SRP-B facets, full invariance was demonstrated. In other words, for these five facets there were no significant changes in \( \Delta \chi^2 \) tests that indicated that the more highly constrained models (i.e., moving from the configural invariance model to the metric invariance model) fit the data worse. Notably, for the PC-B, PC-C, and SRP-B facets invariance was shown to the level of equal latent means. For the IR, PC-A, and SRP-A facets invariance was demonstrated to the point of equal factor variances, but in the subsequent stage of equal factor mean there were significant changes in model-data fit.

There was a slightly more complex set of results for the PC-A, OSR, and SRP-C facets that involved estimating partial invariance models. For the PC-A facet, imposing the constraints of the strict invariance model on the residual variances resulted in a significant decrease in fit. Thus, although PC-A demonstrated configural, metric, and strong invariance, the test of strict invariance was failed due to one substantially different residual variance across time. Freeing the equality constraint on one residual variance therefore allowed for partial strict invariance, \( \Delta \chi^2(5) \)
Table A43

*Longitudinal Measurement Invariance Analysis of the WRI’s PC-A Facet*

<table>
<thead>
<tr>
<th>Mode</th>
<th>$\chi^2$</th>
<th>$\chi^2 c$</th>
<th>$\chi^2 df$</th>
<th>#fp</th>
<th>CFI</th>
<th>RMSEA</th>
<th>$\Delta\chi^2$</th>
<th>$\Delta\chi^2 df$</th>
<th>$\Delta$CFI</th>
<th>$\Delta$RMSEA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Configural</td>
<td>42.184***</td>
<td>.698</td>
<td>15</td>
<td>39</td>
<td>.890</td>
<td>.128 (.084 - .175)</td>
<td>--</td>
<td>--</td>
<td>--</td>
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</tr>
<tr>
<td>Metric</td>
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<td>35</td>
<td>.930</td>
<td>.091 (.044 - .136)</td>
<td>.733</td>
<td>4</td>
<td>.040</td>
<td>-.037</td>
</tr>
<tr>
<td>Strong</td>
<td>41.984***</td>
<td>.894</td>
<td>23</td>
<td>31</td>
<td>.923</td>
<td>.087 (.043 - .128)</td>
<td>6.071</td>
<td>4</td>
<td>-.006</td>
<td>-.004</td>
</tr>
<tr>
<td>Strict</td>
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<td>25</td>
<td>.859</td>
<td>.104 (.070 - .139)</td>
<td>23.128***</td>
<td>6</td>
<td>-.064</td>
<td>.017</td>
</tr>
<tr>
<td>Partial Strict</td>
<td>47.656*</td>
<td>.982</td>
<td>28</td>
<td>26</td>
<td>.920</td>
<td>.080 (.038 - .118)</td>
<td>6.680</td>
<td>5</td>
<td>-.003</td>
<td>-.044</td>
</tr>
<tr>
<td>Factor variance/covariance</td>
<td>47.854*</td>
<td>.989</td>
<td>30</td>
<td>24</td>
<td>.928</td>
<td>.074 (.029 - .111)</td>
<td>.483</td>
<td>2</td>
<td>.007</td>
<td>-.006</td>
</tr>
<tr>
<td>Factor means</td>
<td>54.859**</td>
<td>.995</td>
<td>32</td>
<td>22</td>
<td>.907</td>
<td>.081 (.042 - .116)</td>
<td>6.684*</td>
<td>2</td>
<td>-.020</td>
<td>.007</td>
</tr>
</tbody>
</table>

*Note.* $\chi^2 c$ = scaling correction factor for $\chi^2$; $df$ = degrees of freedom; #fp = number of parameters estimated in each model; CFI = comparative fit index; RMSEA = root mean square error of approximation; $\Delta\chi^2$ = Satorra-Bentler scaled $\chi^2$ difference statistic; $\Delta\chi^2 df$ = degrees of freedom for Satorra-Bentler $\Delta\chi^2$; $\Delta$CFI = change in CFI estimate from less restricted to more restricted models (i.e., change in CFI from configural invariance model to metric invariance model); $\Delta$RMSEA = change in RMSEA estimate from less restricted to more restricted model. The partial strict invariance model is compared to the strong invariance model. The factor variance/covariance and factor mean invariance models are more restrictive models than the partial strict invariance model. * $p < .05,$ ** $p < .01,$ *** $p < .001.$
Table A44

**Longitudinal Measurement Invariance Analysis of the WRI’s PC-B Facet**

<table>
<thead>
<tr>
<th></th>
<th>$\chi^2$</th>
<th>$\chi^2c$</th>
<th>$\chi^2 df$</th>
<th>#fp</th>
<th>CFI</th>
<th>RMSEA</th>
<th>$\Delta\chi^2$</th>
<th>$\Delta\chi^2 df$</th>
<th>$\Delta$CFI</th>
<th>$\Delta$RMSEA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Configural</td>
<td>36.093**</td>
<td>.917</td>
<td>15</td>
<td>39</td>
<td>.927</td>
<td>.113 (.066 - .161)</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Metric</td>
<td>35.797*</td>
<td>1.004</td>
<td>19</td>
<td>35</td>
<td>.942</td>
<td>.090 (.042 - .134)</td>
<td>2.136</td>
<td>4</td>
<td>.015</td>
<td>-.023</td>
</tr>
<tr>
<td>Strong</td>
<td>38.009*</td>
<td>.999</td>
<td>23</td>
<td>31</td>
<td>.948</td>
<td>.077 (.027 - .119)</td>
<td>2.090</td>
<td>4</td>
<td>.006</td>
<td>-.013</td>
</tr>
<tr>
<td>Strict</td>
<td>42.256</td>
<td>1.160</td>
<td>29</td>
<td>25</td>
<td>.954</td>
<td>.064 (.000 - .104)</td>
<td>6.216</td>
<td>6</td>
<td>.006</td>
<td>-.013</td>
</tr>
<tr>
<td>Factor variance/covariance</td>
<td>43.003</td>
<td>1.140</td>
<td>31</td>
<td>23</td>
<td>.958</td>
<td>.059 (.000 - .099)</td>
<td>.002</td>
<td>2</td>
<td>.004</td>
<td>-.005</td>
</tr>
<tr>
<td>Factor means</td>
<td>43.926</td>
<td>1.124</td>
<td>33</td>
<td>21</td>
<td>.962</td>
<td>.055 (.000 - .094)</td>
<td>.411</td>
<td>2</td>
<td>.004</td>
<td>-.004</td>
</tr>
</tbody>
</table>

*Note: $\chi^2c$ = scaling correction factor for $\chi^2$; df = degrees of freedom; #fp = number of parameters estimated in each model; CFI = comparative fit index; RMSEA = root mean square error of approximation; $\Delta\chi^2$ = Satorra-Bentler scaled $\chi^2$ difference statistic; $\Delta\chi^2 df$ = degrees of freedom for Satorra-Bentler $\Delta\chi^2$; $\Delta$CFI = change in CFI estimate from less restricted to more restricted models (i.e., change in CFI from configural invariance model to metric invariance model); $\Delta$RMSEA = change in RMSEA estimate from less restricted to more restricted model. * $p < .05$, ** $p < .01$, *** $p < .001$. 
### Table A45

**Longitudinal Measurement Invariance Analysis of the WRI’s PC-C Facet**

<table>
<thead>
<tr>
<th></th>
<th>$\chi^2$</th>
<th>$\chi^2_c$</th>
<th>$\chi^2_{df}$</th>
<th>#fp</th>
<th>CFI</th>
<th>RMSEA</th>
<th>$\Delta\chi^2$</th>
<th>$\Delta\chi^2_{df}$</th>
<th>$\Delta$CFI</th>
<th>$\Delta$RMSEA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Configural</td>
<td>11.317</td>
<td>.949</td>
<td>15</td>
<td>39</td>
<td>1.000</td>
<td>.000 (.000 - .067)</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Metric</td>
<td>17.128</td>
<td>.937</td>
<td>19</td>
<td>35</td>
<td>1.000</td>
<td>.000 (.000 - .075)</td>
<td>5.958</td>
<td>4</td>
<td>.000</td>
<td>.000</td>
</tr>
<tr>
<td>Strong</td>
<td>20.867</td>
<td>.935</td>
<td>23</td>
<td>31</td>
<td>1.000</td>
<td>.000 (.000 - .070)</td>
<td>3.740</td>
<td>4</td>
<td>.000</td>
<td>.000</td>
</tr>
<tr>
<td>Strict</td>
<td>23.424</td>
<td>1.040</td>
<td>29</td>
<td>25</td>
<td>1.000</td>
<td>.000 (.000 - .053)</td>
<td>3.361</td>
<td>6</td>
<td>.000</td>
<td>.000</td>
</tr>
<tr>
<td>Factor variance/covariance</td>
<td>25.219</td>
<td>1.015</td>
<td>31</td>
<td>23</td>
<td>1.000</td>
<td>.000 (.000 - .052)</td>
<td>1.897</td>
<td>2</td>
<td>.000</td>
<td>.000</td>
</tr>
<tr>
<td>Factor means</td>
<td>26.575</td>
<td>1.027</td>
<td>33</td>
<td>21</td>
<td>1.000</td>
<td>.000 (.000 - .049)</td>
<td>1.398</td>
<td>2</td>
<td>.000</td>
<td>.000</td>
</tr>
</tbody>
</table>

*Note:* $\chi^2_c$ = scaling correction factor for $\chi^2$; df = degrees of freedom; #fp = number of parameters estimated in each model; CFI = comparative fit index; RMSEA = root mean square error of approximation; $\Delta\chi^2$ = Satorra-Bentler scaled $\chi^2$ difference statistic; $\Delta\chi^2_{df}$ = degrees of freedom for Satorra-Bentler $\Delta\chi^2$; $\Delta$CFI = change in CFI estimate from less restricted to more restricted models (i.e., change in CFI from configural invariance model to metric invariance model); $\Delta$RMSEA = change in RMSEA estimate from less restricted to more restricted model. * $p < .05$, ** $p < .01$, *** $p < .001$. 
Table A46

**Longitudinal Measurement Invariance Analysis of the WRI’s OSR Facet**

<table>
<thead>
<tr>
<th>Model</th>
<th>$\chi^2$</th>
<th>$\chi^2_c$</th>
<th>$\chi^2_{df}$</th>
<th>#fp</th>
<th>CFI</th>
<th>RMSEA</th>
<th>$\Delta\chi^2$</th>
<th>$\Delta\chi^2_{df}$</th>
<th>$\Delta$CFI</th>
<th>$\Delta$RMSEA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Configural</td>
<td>46.647***</td>
<td>.935</td>
<td>15</td>
<td>39</td>
<td>.952</td>
<td>.138 (.095 - .184)</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Metric</td>
<td>62.556***</td>
<td>.915</td>
<td>19</td>
<td>35</td>
<td>.934</td>
<td>.144 (.106 - .185)</td>
<td>16.214**</td>
<td>4</td>
<td>-.018</td>
<td>-.013</td>
</tr>
<tr>
<td>Partial Metric</td>
<td>50.278***</td>
<td>.946</td>
<td>18</td>
<td>36</td>
<td>.951</td>
<td>.128 (.087 - .170)</td>
<td>3.968</td>
<td>3</td>
<td>-.001</td>
<td>-.035</td>
</tr>
<tr>
<td>Strong</td>
<td>52.843***</td>
<td>.924</td>
<td>22</td>
<td>32</td>
<td>.953</td>
<td>.113 (.074 - .152)</td>
<td>1.484</td>
<td>4</td>
<td>.002</td>
<td>-.015</td>
</tr>
<tr>
<td>Strict</td>
<td>57.326***</td>
<td>1.083</td>
<td>25</td>
<td>29</td>
<td>.951</td>
<td>.108 (.071 - .146)</td>
<td>5.896</td>
<td>3</td>
<td>-.002</td>
<td>-.005</td>
</tr>
<tr>
<td>Factor variance/</td>
<td>60.226***</td>
<td>1.074</td>
<td>27</td>
<td>27</td>
<td>.950</td>
<td>.106 (.070 - .142)</td>
<td>2.717</td>
<td>2</td>
<td>-.001</td>
<td>-.002</td>
</tr>
<tr>
<td>Factor means</td>
<td>61.385***</td>
<td>1.073</td>
<td>29</td>
<td>25</td>
<td>.951</td>
<td>.101 (.065 - .136)</td>
<td>1.108</td>
<td>2</td>
<td>.001</td>
<td>-.005</td>
</tr>
</tbody>
</table>

*Note.* $\chi^2_c$ = scaling correction factor for $\chi^2$; $df$ = degrees of freedom; #fp = number of parameters estimated in each model; CFI = comparative fit index; RMSEA = root mean square error of approximation; $\Delta\chi^2$ = Satorra-Bentler scaled $\chi^2$ difference statistic; $\Delta\chi^2_{df}$ = degrees of freedom for Satorra-Bentler $\Delta\chi^2$; $\Delta$CFI = change in CFI estimate from less restricted to more restricted models (i.e., change in CFI from configural invariance model to metric invariance model); $\Delta$RMSEA = change in RMSEA estimate from less restricted to more restricted model. The partial metric invariance model is compared to the configural invariance model. The strong, strict, factor variance/covariance, and factor mean invariance models are more restrictive models than the partial metric invariance model. * $p < .05$, ** $p < .01$, *** $p < .001$. 
Table A47

Longitudinal Measurement Invariance Analysis of the WRI’s IR Facet

<table>
<thead>
<tr>
<th></th>
<th>( \chi^2 )</th>
<th>( \chi^2c )</th>
<th>( \chi^2 df )</th>
<th>#fp</th>
<th>CFI</th>
<th>RMSEA</th>
<th>( \Delta \chi^2 )</th>
<th>( \Delta \chi^2 df )</th>
<th>( \Delta )CFI</th>
<th>( \Delta )RMSEA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Configural</td>
<td>15.976</td>
<td>1.133</td>
<td>15</td>
<td>39</td>
<td>.998</td>
<td>.025 (.000 - .096)</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Metric</td>
<td>20.819</td>
<td>1.044</td>
<td>19</td>
<td>35</td>
<td>.996</td>
<td>.030 (.000 - .091)</td>
<td>5.118</td>
<td>4</td>
<td>-.002</td>
<td>.005</td>
</tr>
<tr>
<td>Strong</td>
<td>25.236</td>
<td>1.057</td>
<td>23</td>
<td>31</td>
<td>.995</td>
<td>.030 (.000 - .087)</td>
<td>4.415</td>
<td>4</td>
<td>-.001</td>
<td>.000</td>
</tr>
<tr>
<td>Strict</td>
<td>35.518</td>
<td>1.088</td>
<td>29</td>
<td>25</td>
<td>.986</td>
<td>.046 (.000 - .091)</td>
<td>9.915</td>
<td>6</td>
<td>-.009</td>
<td>.016</td>
</tr>
<tr>
<td>Factor variance/</td>
<td>37.164</td>
<td>1.073</td>
<td>31</td>
<td>23</td>
<td>.987</td>
<td>.043 (.000 - .088)</td>
<td>1.449</td>
<td>2</td>
<td>.001</td>
<td>-.003</td>
</tr>
<tr>
<td>covariance</td>
<td>Factor means</td>
<td>46.438</td>
<td>1.036</td>
<td>33</td>
<td>21</td>
<td>.971</td>
<td>.061 (.000 - .100)</td>
<td>17.793***</td>
<td>2</td>
<td>-.016</td>
</tr>
</tbody>
</table>

*Note: \( \chi^2c \) = scaling correction factor for \( \chi^2 \); \( df \) = degrees of freedom; #fp = number of parameters estimated in each model; CFI = comparative fit index; RMSEA = root mean square error of approximation; \( \Delta \chi^2 \) = Satorra-Bentler scaled \( \chi^2 \) difference statistic; \( \Delta \chi^2 df \) = degrees of freedom for Satorra-Bentler \( \Delta \chi^2 \); \( \Delta \)CFI = change in CFI estimate from less restricted to more restricted models (i.e., change in CFI from configural invariance model to metric invariance model); \( \Delta \)RMSEA = change in RMSEA estimate from less restricted to more restricted model. * \( p < .05 \), ** \( p < .01 \), *** \( p < .001 \).
Table A48

*Longitudinal Measurement Invariance Analysis of the WRI’s SRP-A Facet*

<table>
<thead>
<tr>
<th></th>
<th>$\chi^2$</th>
<th>$\chi^2c$</th>
<th>$\chi^2 df$</th>
<th>#fp</th>
<th>CFI</th>
<th>RMSEA</th>
<th>$\Delta\chi^2$</th>
<th>$\Delta\chi^2 df$</th>
<th>$\Delta$CFI</th>
<th>$\Delta$RMSEA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Configural</td>
<td>20.599</td>
<td>1.058</td>
<td>15</td>
<td>39</td>
<td>.978</td>
<td>.059 (.000 - .116)</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Metric</td>
<td>22.355</td>
<td>1.034</td>
<td>19</td>
<td>35</td>
<td>.987</td>
<td>.040 (.000 - .097)</td>
<td>1.410</td>
<td>4</td>
<td>.009</td>
<td>-.019</td>
</tr>
<tr>
<td>Strong</td>
<td>25.244</td>
<td>1.016</td>
<td>23</td>
<td>31</td>
<td>.991</td>
<td>.030 (.000 - .087)</td>
<td>2.724</td>
<td>4</td>
<td>.004</td>
<td>-.010</td>
</tr>
<tr>
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<td>37.076</td>
<td>1.068</td>
<td>29</td>
<td>25</td>
<td>.969</td>
<td>.051 (.000 - .094)</td>
<td>11.012</td>
<td>6</td>
<td>-.023</td>
<td>.021</td>
</tr>
<tr>
<td>Factor variance/covariance</td>
<td>37.451</td>
<td>1.079</td>
<td>31</td>
<td>23</td>
<td>.975</td>
<td>.044 (.000 - .088)</td>
<td>.654</td>
<td>2</td>
<td>.006</td>
<td>-.007</td>
</tr>
<tr>
<td>Factor means</td>
<td>46.466</td>
<td>1.070</td>
<td>33</td>
<td>21</td>
<td>.948</td>
<td>.061 (.000 - .100)</td>
<td>10.017**</td>
<td>2</td>
<td>-.027</td>
<td>.017</td>
</tr>
</tbody>
</table>

*Note: $\chi^2c$ = scaling correction factor for $\chi^2$; df = degrees of freedom; #fp = number of parameters estimated in each model; CFI = comparative fit index; RMSEA = root mean square error of approximation; $\Delta\chi^2$ = Satorra-Bentler scaled $\chi^2$ difference statistic; $\Delta\chi^2 df$ = degrees of freedom for Satorra-Bentler $\Delta\chi^2$; $\Delta$CFI = change in CFI estimate from less restricted to more restricted models (i.e., change in CFI from configural invariance model to metric invariance model); $\Delta$RMSEA = change in RMSEA estimate from less restricted to more restricted model. * p < .05, ** p < .01, *** p < .001.*
Table A49

*Longitudinal Measurement Invariance Analysis of the WRI's SRP-B Facet*

<table>
<thead>
<tr>
<th></th>
<th>$\chi^2$</th>
<th>$\chi^2c$</th>
<th>$\chi^2 df$</th>
<th>#fp</th>
<th>CFI</th>
<th>RMSEA</th>
<th>$\Delta\chi^2$</th>
<th>$\Delta\chi^2 df$</th>
<th>$\Delta$CFI</th>
<th>$\Delta$RMSEA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Configural</td>
<td>42.024***</td>
<td>.828</td>
<td>15</td>
<td>39</td>
<td>.907</td>
<td>.129 (.084 - .176)</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Metric</td>
<td>49.120***</td>
<td>.878</td>
<td>19</td>
<td>35</td>
<td>.897</td>
<td>.121 (.080 - .163)</td>
<td>7.828</td>
<td>4</td>
<td>.011</td>
<td>-.008</td>
</tr>
<tr>
<td>Strong</td>
<td>55.432***</td>
<td>.884</td>
<td>23</td>
<td>31</td>
<td>.889</td>
<td>.114 (.076 - .153)</td>
<td>6.438</td>
<td>4</td>
<td>.008</td>
<td>-.007</td>
</tr>
<tr>
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<td>29</td>
<td>25</td>
<td>.868</td>
<td>.111 (.076 - .145)</td>
<td>12.399</td>
<td>6</td>
<td>.020</td>
<td>-.003</td>
</tr>
<tr>
<td>Factor variance/covariance</td>
<td>66.236***</td>
<td>.956</td>
<td>31</td>
<td>23</td>
<td>.879</td>
<td>.103 (.068 - .137)</td>
<td>.183</td>
<td>2</td>
<td>-.011</td>
<td>-.008</td>
</tr>
<tr>
<td>Factor means</td>
<td>67.819***</td>
<td>.953</td>
<td>33</td>
<td>21</td>
<td>.880</td>
<td>.099 (.065 - .132)</td>
<td>1.469</td>
<td>2</td>
<td>-.001</td>
<td>-.004</td>
</tr>
</tbody>
</table>

*Note:* $\chi^2c = \text{scaling correction factor for } \chi^2$; df = degrees of freedom; #fp = number of parameters estimated in each model; CFI = comparative fit index; RMSEA = root mean square error of approximation; $\Delta\chi^2 = \text{Satorra-Bentler scaled } \chi^2 \text{ difference statistic}$; $\Delta\chi^2 df = \text{degrees of freedom for Satorra-Bentler } \Delta\chi^2$; $\Delta$CFI = change in CFI estimate from less restricted to more restricted models (i.e., change in CFI from configural invariance model to metric invariance model); $\Delta$RMSEA = change in RMSEA estimate from less restricted to more restricted model. * $p < .05$, ** $p < .01$, *** $p < .001$. 
### Table A50

**Longitudinal Measurement Invariance Analysis of the WRI’s SRP-C Facet**

<table>
<thead>
<tr>
<th></th>
<th>$\chi^2$</th>
<th>$\chi^2_c$</th>
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<th>#fp</th>
<th>CFI</th>
<th>RMSEA</th>
<th>$\Delta\chi^2$</th>
<th>$\Delta\chi^2$ df</th>
<th>$\Delta$CFI</th>
<th>$\Delta$RMSEA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Configural</td>
<td>12.491</td>
<td>1.207</td>
<td>15</td>
<td>39</td>
<td>1.000</td>
<td>.000 (.000 - .076)</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Metric</td>
<td>16.385</td>
<td>1.175</td>
<td>19</td>
<td>35</td>
<td>1.000</td>
<td>.000 (.000 - .072)</td>
<td>3.956</td>
<td>4</td>
<td>.000</td>
<td>.000</td>
</tr>
<tr>
<td>Strong</td>
<td>19.317</td>
<td>1.151</td>
<td>23</td>
<td>31</td>
<td>1.000</td>
<td>.000 (.000 - .064)</td>
<td>2.874</td>
<td>4</td>
<td>.000</td>
<td>.000</td>
</tr>
<tr>
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<td>1.041</td>
<td>29</td>
<td>25</td>
<td>.999</td>
<td>.011 (.000 - .074)</td>
<td>13.453*</td>
<td>6</td>
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<td>.011</td>
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<tr>
<td>Partial Strict</td>
<td>24.313</td>
<td>1.075</td>
<td>28</td>
<td>26</td>
<td>1.000</td>
<td>.000 (.000 - .061)</td>
<td>5.378</td>
<td>5</td>
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<tr>
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<td>1.052</td>
<td>30</td>
<td>24</td>
<td>1.000</td>
<td>.000 (.000 - .055)</td>
<td>.147</td>
<td>2</td>
<td>.000</td>
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<td>Factor means</td>
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<td>32</td>
<td>22</td>
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<td>.017 (.000 - .074)</td>
<td>10.214**</td>
<td>2</td>
<td>.003</td>
<td>.017</td>
</tr>
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**Note.** $\chi^2_c$ = scaling correction factor for $\chi^2$; df = degrees of freedom; #fp = number of parameters estimated in each model; CFI = comparative fit index; RMSEA = root mean square error of approximation; $\Delta\chi^2$ = Satorra-Bentler scaled $\chi^2$ difference statistic; $\Delta\chi^2$ df = degrees of freedom for Satorra-Bentler $\Delta\chi^2$; $\Delta$CFI = change in CFI estimate from less restricted to more restricted models (i.e., change in CFI from configural invariance model to metric invariance model); $\Delta$RMSEA = change in RMSEA estimate from less restricted to more restricted model. The partial strict invariance model is compared to the strong invariance model. The factor variance/covariance and factor mean invariance models are more restrictive models than the partial strict invariance model. * $p < .05$, ** $p < .01$, *** $p < .001$. 
Following the partial strict invariance model, imposing the additional constraints on the factor variances did not demonstrated evidence of non-invariance, however in the last stage in equating the factor means, the means were found to be significantly different over time, with Time 2 PC-A slight lower than Time 1, and Time 3 PC-A slightly greater (however, separately $p > .05$). Thus, the PC-A facet demonstrated evidence of partial invariance over time.

The OSR facet failed the $\Delta \chi^2$ test associated with moving from the configural invariance model to the metric invariance model, $\Delta \chi^2(4) = 16.214, p = .003$. This would suggest that the factor loadings of the item parcels might vary over time. Upon inspection of the modification indices and the factor loading estimates from the configural invariance model, I relaxed the equality constraint on one of the Time 1 factor loadings, thus leaving two of the Time 1 loadings estimated to be equal to the respective Time 2 and Time 3 loadings (in addition to the all of the respective Time 2 and Time 3 loadings being estimated as equal). This partial metric invariance model did not demonstrate a significant decrease in model fit from the configural invariance model, and was therefore supported. Building upon this partial metric invariance model, the remainder of invariance analyses did not result in a significant change in model fit. Thus, after accounting for a difference in factor loadings, invariance up to the level of equal latent means was demonstrated for the OSR scale of the WRI.

Longitudinal invariance analyses on the SRP-C facet supported configural, metric, and scalar invariance, but with the inclusion of the equality constraints on the residual variances, the $\Delta \chi^2$ test suggested that full strict invariance was not supported, $\Delta \chi^2(6) = 13.453, p = .036$. Relaxing one of the equality constraints on the Time 3 residual variances allowed the strict invariance test to be passed, thus supporting partial strict invariance, $\Delta \chi^2(5)$
= 5.378, \( p = .371 \). Building upon this partial strict invariance model, a subsequent model that constrained the factor variances to equality over time was then supported, \( \Delta \chi^2(2) = .147, p = .929 \). In the final step of the SRP-C facet’s invariance analyses, the latent means were constrained to equality. The inclusion of these constraints was found to significantly decrease model fit, \( \Delta \chi^2(2) = 10.215, p = .006 \), thus suggesting the latent SRP-C means varied over time. In fact, the SRP-C means exhibited the same pattern of differences (again, albeit \( ps > .05 \)) as the PC-A means described previously: Time 2 was less than Time 1, and Time 3 was greater than Time 1. Thus, partial invariance of the SRP-C facet was demonstrated over time.

**Summary.** These longitudinal MI analyses, conducted on all of current study’s measures, were in effort to ensure that any cross-time comparisons were valid. This issue and motivation was broached in Study 1, and won’t be repeated in detail here. However, to provide a basic frame-of-reference, these MI analyses were necessary to ensure that the constructs assessed by each scale were measured in the same manner, with the same reliability, over time. In other words, these analyses were necessary to show that each measure functioned and meant the same over time (see Balzer, Greguras, & Raymark, 2004). Without showing at least some degree of invariance, as in partial invariance, then any comparisons made across timepoints may not be valid or informative.
Appendix W – Study 2 Latent Difference Power Analyses, Satorra and Saris Method

Table A51

<table>
<thead>
<tr>
<th>Latent Difference Score Power Analyses, Satorra and Saris Method</th>
<th>( n )</th>
<th>( \chi^2 ) (NCP)</th>
<th>Power</th>
<th>( n )</th>
<th>( \chi^2 ) (NCP)</th>
<th>Power</th>
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<td>1.000</td>
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</table>

*Note.* NCP = non-centrality parameter. \( \chi^2 \) or NCP are the model fit fit estimates that are associated with fixing the variance of the respective LDS factors to zero.
Appendix X – Study 2 Latent Difference Power Analyses, Monte Carlo Method

Table A52

<table>
<thead>
<tr>
<th></th>
<th>Time 1 → Time 2 Latent Difference Score Power Analyses, Monte Carlo Method</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Pop. Estimate</td>
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<tr>
<td>PC-A (Factor loading 1)</td>
<td>1.000 (^a)</td>
</tr>
<tr>
<td>PC-A (Factor loading 2)</td>
<td>0.809</td>
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<tr>
<td>PC-A (Factor loading 3)</td>
<td>1.075</td>
</tr>
<tr>
<td>PC-A (LDS σ)</td>
<td>0.077</td>
</tr>
<tr>
<td>PC-B (Factor loading 1)</td>
<td>1.000 (^a)</td>
</tr>
<tr>
<td>PC-B (Factor loading 2)</td>
<td>0.855</td>
</tr>
<tr>
<td>PC-B (Factor loading 3)</td>
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</tr>
<tr>
<td>PC-B (LDS σ)</td>
<td>0.065</td>
</tr>
<tr>
<td>PC-C (Factor loading 1)</td>
<td>1.000 (^a)</td>
</tr>
<tr>
<td>PC-C (Factor loading 2)</td>
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<td>PC-C (Factor loading 3)</td>
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<tr>
<td>PC-C (LDS σ)</td>
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<tr>
<td>IR (Factor loading 1)</td>
<td>1.000 (^a)</td>
</tr>
<tr>
<td>IR (Factor loading 2)</td>
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<td>IR (Factor loading 3)</td>
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<td>IR (LDS σ)</td>
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<tr>
<td>OSR (Factor loading 1)</td>
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<tr>
<td>OSR (Factor loading 2)</td>
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<td>OSR (Factor loading 3)</td>
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<td>OSR (LDS σ)</td>
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<tr>
<td>SRP-A (Factor loading 1)</td>
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<td>SRP-A (Factor loading 2)</td>
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<tr>
<td>SRP-A (Factor loading 3)</td>
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<tr>
<td>SRP-A (LDS σ)</td>
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Note. \(^a\) parameter fixed for identification purposes. Coverage = % of replications for which 95% CI contains population value, indicates how well parameters (and SEs) are estimated.
### Time 1 → Time 2 Latent Difference Score Power Analyses, Monte Carlo Method

<table>
<thead>
<tr>
<th></th>
<th>Pop. Estimate</th>
<th>MC Estimate</th>
<th>Coverage</th>
<th>Absolute Bias (%)</th>
</tr>
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<tr>
<td><strong>SRP-B</strong></td>
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<td></td>
</tr>
<tr>
<td>Factor loading 1</td>
<td>1.000^a</td>
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<td>1.000</td>
<td>0.000</td>
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<tr>
<td>Factor loading 2</td>
<td>0.915</td>
<td>0.922</td>
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<tr>
<td>Factor loading 3</td>
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<td>0.816</td>
<td>0.948</td>
<td>0.086</td>
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<tr>
<td>LDS σ</td>
<td>0.042</td>
<td>0.041</td>
<td>0.938</td>
<td>1.667</td>
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</tr>
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<tr>
<td><strong>JSSE</strong></td>
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<tr>
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<td><strong>PsyCap</strong></td>
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<tr>
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<td>0.062</td>
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*Note.* ^a parameter fixed for identification purposes. Coverage = % of replications for which 95% CI contains population value, indicates how well parameters (and SEs) are estimated.
Table A53

**Time 2 → Time 3 Latent Difference Score Power Analyses, Monte Carlo Method**

<table>
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<tr>
<th></th>
<th>Pop. Estimate</th>
<th>MC Estimate</th>
<th>Coverage</th>
<th>Absolute Bias (%)</th>
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<td><strong>PC-A</strong></td>
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*Note.* <sup>a</sup> Parameter fixed for identification purposes. Coverage = % of replications for which 95% CI contains population value, indicates how well parameters (and SEs) are estimated.
Table A53, continued

*Time 2 → Time 3 Latent Difference Score Power Analyses, Monte Carlo Method*

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<thead>
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<th></th>
<th>Pop. Estimate</th>
<th>MC Estimate</th>
<th>Coverage</th>
<th>Absolute Bias (%)</th>
</tr>
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<tbody>
<tr>
<td><strong>SRP-B</strong></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Factor loading 1</td>
<td>1.000&lt;sup&gt;a&lt;/sup&gt;</td>
<td>1.000</td>
<td>1.000</td>
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<tr>
<td>Factor loading 2</td>
<td>0.870</td>
<td>0.875</td>
<td>0.936</td>
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<td>Factor loading 3</td>
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<td>0.804</td>
<td>0.948</td>
<td>0.137</td>
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<tr>
<td>LDS σ</td>
<td>0.053</td>
<td>0.051</td>
<td>0.924</td>
<td>3.208</td>
</tr>
<tr>
<td><strong>SRP-C</strong></td>
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</tr>
<tr>
<td>Factor loading 1</td>
<td>1.000&lt;sup&gt;a&lt;/sup&gt;</td>
<td>1.000</td>
<td>1.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Factor loading 2</td>
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<td>0.935</td>
<td>0.926</td>
<td>0.538</td>
</tr>
<tr>
<td>Factor loading 3</td>
<td>0.749</td>
<td>0.750</td>
<td>0.954</td>
<td>0.187</td>
</tr>
<tr>
<td>LDS σ</td>
<td>0.120</td>
<td>0.116</td>
<td>0.910</td>
<td>3.583</td>
</tr>
<tr>
<td><strong>PWB</strong></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Factor loading 1</td>
<td>1.000&lt;sup&gt;a&lt;/sup&gt;</td>
<td>1.000</td>
<td>1.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Factor loading 2</td>
<td>0.753</td>
<td>0.752</td>
<td>0.930</td>
<td>0.159</td>
</tr>
<tr>
<td>Factor loading 3</td>
<td>0.866</td>
<td>0.859</td>
<td>0.950</td>
<td>0.774</td>
</tr>
<tr>
<td>LDS σ</td>
<td>0.034</td>
<td>0.033</td>
<td>0.920</td>
<td>2.647</td>
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<tr>
<td><strong>JSSE</strong></td>
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<td></td>
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<td></td>
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<tr>
<td>Factor loading 1</td>
<td>1.000&lt;sup&gt;a&lt;/sup&gt;</td>
<td>1.000</td>
<td>1.000</td>
<td>0.000</td>
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<tr>
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<td>0.996</td>
<td>1.002</td>
<td>0.926</td>
<td>0.572</td>
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<tr>
<td>Factor loading 3</td>
<td>1.074</td>
<td>1.076</td>
<td>0.964</td>
<td>0.205</td>
</tr>
<tr>
<td>LDS σ</td>
<td>0.048</td>
<td>0.045</td>
<td>0.912</td>
<td>5.625</td>
</tr>
<tr>
<td><strong>PsyCap</strong></td>
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<td></td>
</tr>
<tr>
<td>Factor loading 1</td>
<td>1.000&lt;sup&gt;a&lt;/sup&gt;</td>
<td>1.000</td>
<td>1.000</td>
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</tr>
<tr>
<td>Factor loading 2</td>
<td>1.140</td>
<td>1.139</td>
<td>0.934</td>
<td>0.053</td>
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<tr>
<td>Factor loading 3</td>
<td>0.924</td>
<td>0.929</td>
<td>0.934</td>
<td>0.530</td>
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<td>Factor loading 4</td>
<td>0.989</td>
<td>0.991</td>
<td>0.958</td>
<td>0.212</td>
</tr>
<tr>
<td>LDS σ</td>
<td>0.070</td>
<td>0.070</td>
<td>0.894</td>
<td>0.714</td>
</tr>
</tbody>
</table>

*Note.*<sup>a</sup> parameter fixed for identification purposes. Coverage = % of replications for which 95% CI contains population value, indicates how well parameters (and SEs) are estimated.
Appendix Y – Study 2 Latent Difference Score Regression Power Analyses

Table A54

**LDS Regression Power Analyses**

<table>
<thead>
<tr>
<th></th>
<th>$R^2$</th>
<th>$f^2$</th>
<th>$\Delta R^2$</th>
<th>$\Delta f^2$</th>
<th>Power</th>
<th>Power, $\Delta$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time 1 $\rightarrow$ Time 2 PWB</td>
<td>.302</td>
<td>.433</td>
<td>.031</td>
<td>.046</td>
<td>.999</td>
<td>.548</td>
</tr>
<tr>
<td>Time 2 $\rightarrow$ Time 3 PWB</td>
<td>.166</td>
<td>.199</td>
<td>.000</td>
<td>.000</td>
<td>.897</td>
<td>.054</td>
</tr>
<tr>
<td>Time 2 $\rightarrow$ Time 3 PWB</td>
<td>.335</td>
<td>.504</td>
<td>.057</td>
<td>.094</td>
<td>1.000</td>
<td>.840</td>
</tr>
<tr>
<td>Time 1 $\rightarrow$ Time 2 JSSE</td>
<td>.203</td>
<td>.255</td>
<td>.011</td>
<td>.014</td>
<td>.961</td>
<td>.206</td>
</tr>
<tr>
<td>Time 2 $\rightarrow$ Time 3 JSSE</td>
<td>.086</td>
<td>.094</td>
<td>.006</td>
<td>.007</td>
<td>.525</td>
<td>.122</td>
</tr>
<tr>
<td>Time 2 $\rightarrow$ Time 3 JSSE</td>
<td>.205</td>
<td>.258</td>
<td>.039</td>
<td>.052</td>
<td>.963</td>
<td>.587</td>
</tr>
</tbody>
</table>

*Note. Cohen’s (1988) conventions for $f^2$: small = .02, medium = .15, large = .35.*
Appendix Z – Correlations Between Scores Exported From Invariant Longitudinal Confirmatory Factor Analyses Across Study 1 and Study 2 Samples

Table A55

Correlations Between Latent Variable Scores Between Full Study 2 Sample and the Reduced Study 2 Sample After Demonstrating Strict Invariance to Study 1’s Longitudinal Data

<table>
<thead>
<tr>
<th></th>
<th>Time 1</th>
<th>Time 2</th>
<th>Time 3&lt;sup&gt;a&lt;/sup&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td>PWB</td>
<td>.951</td>
<td>.945</td>
<td>.879</td>
</tr>
<tr>
<td>PC-A</td>
<td>.976</td>
<td>.924</td>
<td>.880</td>
</tr>
<tr>
<td>PC-B</td>
<td>.955</td>
<td>.984</td>
<td>.873</td>
</tr>
<tr>
<td>PC-C</td>
<td>.987</td>
<td>.982</td>
<td>.899</td>
</tr>
<tr>
<td>OSR</td>
<td>.977</td>
<td>.956</td>
<td>.747</td>
</tr>
<tr>
<td>IR</td>
<td>.993</td>
<td>.991</td>
<td>.745</td>
</tr>
<tr>
<td>SRP-A</td>
<td>.934</td>
<td>.927</td>
<td>.809</td>
</tr>
<tr>
<td>SRP-B</td>
<td>.991</td>
<td>.995</td>
<td>.925</td>
</tr>
<tr>
<td>SRP-C</td>
<td>.985</td>
<td>.987</td>
<td>.830</td>
</tr>
</tbody>
</table>

<sup>a</sup> Although Time 3 correlations are lower in magnitude, this was to be expected given that they were equated to Time 2 of Study 1 because Study 1 did not include a third assessment. Since strict invariance was supported these correlations are provided for the sake of completion.
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