Affectivity and its Role in Predicting Sociometric Position in Small Group Networks

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Abstract

An individual’s tendency to experience positive emotions can impact the likelihood they find themselves in advantageous positions within their social circle. Adopting a network perspective to map social relations, the current study examined the extent to which dispositional positive affectivity predicts one’s eigenvector centrality and indegree centrality within interaction networks and status networks, respectively. Gathering data during the Fall of 2023, I collected data from 16 student clubs and the members within them and utilised multilevel modeling to disaggregate data. Controlling for individual demographics and group-structure variables, the results suggest that dispositional positive affectivity significantly predicted eigenvector centrality for interaction networks, but not indegree centrality for status networks. Negative affectivity was found to predict indegree centrality for status networks, but not eigenvector centrality for interaction networks. Group-aggregated positive affectivity was not significant in predicting average interaction network centrality but was significant for indegree status network centrality. Group-aggregated negative affectivity failed to predict for both networks. My thesis therefore demonstrates the importance of considering individuals’ affect to explain how people come to position themselves within small social circles, whilst also descriptively highlighting the differences between interaction and status networks.

Keywords: Positive affectivity; Peer nomination; Social network analysis; Multilevel
Summary for Lay Audience

Dispositional positive affectivity is described as the stable tendency for a person to experience and respond to situations in a positive way. Individuals with this tendency often attract attention in social settings and readily make social connections. Despite our understanding of the social outcomes associated with dispositional affect, we know very little about the processes that occur as people form social connections in small groups. This study examined how dispositional affect impacts the way an individual position themselves within small groups.

To evaluate the correlates of dispositional affect, I collected data from members of 16 student clubs at Western University during the Fall term of 2023. Data was collected in-person over the course of two months whilst clubs had their regular meeting. Club members named up to 10 members with whom they spend time or interact away from the club environment, and 5 individuals that were respected and admired by group members. Using these nominations, I constructed a network to determine each member’s position within their club: Those receiving many nominations for interactions were considered more embedded (or popular), while those with many status nominations were considered high-status. I then measured participants’ beliefs about their dispositional affect and other demographic information.

Club members who possessed more dispositional positive affectivity were found to occupy more integral and important positions for friendship social circles within the clubs. However, the same was not found for status: Club members who lacked dispositional negative affectivity were found to situate themselves into central and popular positions. This research provides insight into the mechanisms that contribute to how ‘positive individuals’ come to form their large social networks and furthers our understanding on how dispositional affect plays a different role for affiliative and status social connection.
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## Table of Contents

Abstract ........................................................................................................................................ ii
Acknowledgements ................................................................................................................ iv
Table of Contents ..................................................................................................................... v
List of Tables .......................................................................................................................... vi
List of Figures ............................................................................................................................. vii
List of Appendices ...................................................................................................................... viii
Affectivity and its Role in Determining One’s Position in a Social Network ......................... 1
  Organizations and Small Group Relationships as Networks ................................................. 2
  Social Network Analysis .......................................................................................................... 4
  Personality and Structural Positions within Networks ......................................................... 7
  Positive Affectivity and Socialization ..................................................................................... 14
The Current Study .................................................................................................................... 17
  Predicting Individual Structural Position Using Personal Characteristics .................. 20
  Predicting Group Structure .................................................................................................. 21
  Group Context Interacts with Individual-level Association ........................................... 22
Method ...................................................................................................................................... 23
  Participants .............................................................................................................................. 23
  Procedure ............................................................................................................................... 24
  Measures ................................................................................................................................. 25
  Analyses .................................................................................................................................... 27
Results ...................................................................................................................................... 31
  Characterizing Club Networks ............................................................................................ 31
  Descriptive Data ...................................................................................................................... 37
  Multilevel Models ................................................................................................................... 41
Discussion ................................................................................................................................. 46
Future Research/Limitations .................................................................................................... 54
References ................................................................................................................................. 59
List of Tables

Table 1. Meta-analytic Regression Models for Personality and Network position………………..11
Table 2. Relevant Network Variables Leveraged in This Research…………………………………19
Table 3. Bivariate Correlations and Descriptive Statistics for Within and Between-level Study
Variables……………………………………………………………………………………………………………………………40
Table 4. Multilevel Regression Models (w/ ML) Predicting Eigenvector Centrality for Interaction
Nominations…………………………………………………………………………………………………………………………43
Table 5. Multilevel Poisson Regression Models (w/ML) Predicting Indegree Centrality for Status
Nomination…………………………………………………………………………………………………………………………45
Table 6. Contrast Between Individual-level Predictors’ Impact on Interaction and Status
Networks…………………………………………………………………………………………………………………………51
List of Figures

Figure 1. Flow Chart of Club Participation and Data.........................................................24
Figure 2. Histogram of Participation Rate of Clubs for Interaction Network......................34
Figure 3. Histogram of Participation Rate of Clubs for Status Network..............................34
Figure 4. Two Illustrative Network Graphs of Interaction Networks.................................35
Figure 5. Two Illustrative Network Graphs of Status Networks........................................36
List of Appendices

Appendix A. Peer Interaction Nomination.................................................................67
Appendix B. Peer Status Nomination.................................................................68
Appendix C. Emotional Reactivity, Intensity, and Preservation Scale.........................69
Appendix D. Demographics Questionnaire..........................................................70
Appendix E. Reactivity Justification....................................................................71
Appendix F. Mplus Code for Multilevel Analysis...................................................72
Appendix G. Ethics Approval.............................................................................73
Appendix H. Curriculum Vitae for Roy Hui............................................................74
Affectivity and its Role in Determining One’s Position in a Social Network

In social situations, we are highly attentive toward others’ emotional displays. Humans attend to emotional displays of others for many functions, including to anticipate others’ intentions and to cooperate on shared tasks (Keltner, Tracy, & Cowen, 2019). Emotional displays are also a tool that we use intentionally in social interactions to develop affiliations and influence (or manipulate) others. As an example of how the power of emotional display is entrenched in popular culture, recommendations in the 1998 self-help book ‘How to win friends and influence others’ include being to ‘smile’ (to make people like you) and to ‘begin in a friendly way’ (to influence others’ thinking; Carnegie, 2009). This pattern also bears out empirically because positivity is one key factor predicting leadership emergence in small groups (Joseph et al., 2015).

Positive affect is, therefore, a key social signal to which people attend and is an important factor shaping small group interactions.

The present research applies this insight to better understand positive affectivity within groups, as a disposition reflecting stable individual differences in the extent to which an individual experiences positive emotion (Watson & Naragon, 2009). Whereas there is evidence that those high in positive affectivity gain affiliations and status in organizations, current studies involving positive affectivity have focused primarily on the individual level of analysis. Existing studies therefore leave us with little understanding regarding how context shapes current findings and little clarity about which aspects of group structure may relate to positive affectivity.

Adopting a multilevel lens, the current research focuses on the extent to which individual-level positive affectivity and team composition relates to the informal social structures of interaction and status within student clubs. I capture social structure through member nominations of peers, which enables a social network approach to understand where each member is positioned in their
group as well as the structure of ties in the group as a whole. In this introduction, I will provide a brief overview on the concepts studied in my thesis. First, I will highlight the complexity of small groups in organisations and how structural aspects can indirectly and directly impact how group members interact. Following that, I will justify my adoption of a network approach in studying social relationships by highlighting past research that demonstrating the link between personality and social group/network position. Lastly, I will introduce positive affectivity as a trait predicting sociometric position in small groups.

**Organizations and Small Group Relationships as Networks**

Psychologists have often seen small groups as critical microcosms to examine fundamental processes governing social interactions – defining small groups as a collection of members who interact with one another directly, while sharing sources of interdependence along with an overarching group structure. This interest into small groups and the way in which they function extends to the early 21st century and the post-war era, with exemplars being Sherif’s (1936) experiments examining the development of group norms and Whyte’s (1943) case studies of youth gangs in America. One example of a dominant strand of small groups research involves intergroup research, examining psychological boundaries that distinguish people based on group memberships and that fundamentally alter how they interact with others (Hogg, 1987). Small groups research is also importantly focused on understanding the nature of interactions within small groups, termed small group dynamics research. The popularity of the study of small group dynamics has, admittedly, varied; initial enthusiasm for small group dynamics research in social psychology and sociology waned in recent decades to the extent that some scholars claimed that group dynamics as a domain of study was figuratively ‘dead’ (e.g., Harrington & Fine, 2000).
In contrast, Mathieu and colleagues (2017) documented how the prevalence and diversity of groups research within organizational psychology has grown in recent decades (Harrington & Fine, 2000; Mathieu et al., 2017). Small groups are significant because they are figuratively everywhere. Within the workplace, small groups form for a myriad of reasons and purposes: As essential units for completing projects and achieving goals, to provide enjoyable activities, to provide social support, and even to experience a sense of connection with groups and the entire organization. Small groups are also widespread in society to the extent that they are the context for interactions at work, but also in the community, in education, and in recreation. The value of small groups research is further bound in the recognition that groups often shape members’ interactions. For example, researchers have documented how members’ behaviours are connected, interdependent and share consequences (Hackman, 1992).

When moving from ‘why’ we study groups toward ‘how’ they are studied in organizations, Mathieu and colleagues (2017) reviewed teams research and classified existing group dynamics constructs as being mediating mechanisms (i.e., emergent states and group processes), structural constructs, or compositional constructs. The authors emphasized how emergent states and group processes – concepts like cohesion or communication – are central to the study of groups because they distinguish how members feel about and function as a team. Group composition and structure are nevertheless also important research topics because they help predict how members will interact and influence one another. The former involves distinguishing the characteristics of people within groups at an individual and group level, and how such composition can influence other concepts like member satisfaction and performance. Meanwhile, the study of group structure pertains to the social structure that defines group members’ relations to each other over time. Social structures can be formalized in nature via the
group task or group design (e.g., the structure of interdependence regarding how members must work). Of interest to me, structures are also emergent and informal patterns that reflect how members actually interact and view one-another.

Applying this distinction from Mathieu and colleagues (2017), my thesis focuses on two of the primary topic areas within small groups research: (a) member characteristics and group composition; and (b) group structure. My thesis focuses on the extent to which personal characteristics and team composition shape the informal social structures of interaction and status; examining how individual members come to occupy certain positions within their social groups, and how variability in group composition shapes their social structures. My research deduces group structure by analyzing peer nominations; I apply a social network approach as my prevailing conceptual and methodological lens for studying small groups.

**Social Network Analysis**

Relationships in small groups are commonly organized as complex structures, where members’ social positions differ from one another and where members are expected to be most readily influenced by one-another who are most proximal to them (i.e., directly interacting or related). Such interactions often unfold as relational networks in which the very experience of a ‘group’ is generated through sets of interactions among each member. These networks are first important to recognize as a way of capturing the environment in a group, in the sense that they can help understand the overarching closeness of members. These networks are also important to capture because they help to understand the position that an individual occupies within their group. In organizations, employees can benefit from occupying advantageous positions within a network. When members are closely connected with many others within their groups at work or in broader organizations, they can gain access to knowledge, social support, and other resources
necessary for work performance and career success (Baldwin et al. 1997; Fang et al., 2015; Gibbons 2004). This tendency for social structures to emerge and impact individual members pertains to numerous types of interactions in small groups.

By recognizing that interpersonal networks represent the scaffolding upon which organizations and networks function, unique methodologies must be brought to bear to answer network-related questions. When using traditional (i.e., non-network based) self-report sample surveys to assess relationships between members or social climates, researchers commonly examine questions pertaining to: (a) individual-level constructs reflecting each members’ own perception of the group, or behaviour within the group, and (b) group-level data that is aggregated data across all individuals or captured at a group level. Groups researchers have adopted several methodological tools to improve our ability to understand group member interactions while also reducing statistical artefacts that emerge when participants’ data shares variability with group members. Alongside other widely used strategies, network analyses are increasingly implemented by industrial/organisational researchers to investigate network structures and infer potential meaning regarding one’s position within a social network. Over the last quarter century, work team researchers have began adopting and implementing a social network lens to account for the complexity and dynamic nature of teams (Park et al., 2018).

The value of a network-related approach is evident when reflecting on the strengths and limitations of multilevel approaches. Multilevel modeling addresses the methodological challenges that arise when clustered data violate the statistical assumption that one individual’s data is independent from all others. This approach is useful in unpacking within-team variance, while also unpacking group-level processes and outcomes that may be multilevel in nature (e.g., group context moderating individual-level associations). However, a fundamental issue with
multilevel modeling when applied to data to the exclusion of other analyses is the risk of assuming that all members of the group experience (or are influenced by) their group in relatively homogeneous ways.

As an analogy, consider people at a live music event who all experience the same show but likely form diverse perspectives of the experience. Some of this diversity could be a result of their individual differences, but some diversity could be shared by certain individuals based on who they attended the event with or where they were located (e.g., beside noisy patrons; behind a group of taller people; close to the restroom). Group members are similarly tethered to one another through shared experiences and processes, and each member has a unique vantage of their group that provides nuance. Social network approaches acknowledge how members who are tied to one another to a greater extent (e.g., interact more frequently) will produce data that is more interdependent with one-another than with the group as a whole. Building from this reasoning, several organizational scholars have espoused key applications for network approaches and emphasized the need to increasingly integrate network approaches. For instance, Mathieu & Chen (2011) acknowledged network approaches in their call for a paradigm shift when they wrote “network approaches […] may prove valuable for generating alternative paradigms on which new multilevel quantitative investigations and methodologies could be advanced” (p. 626).

One fruitful approach to utilize network approaches is to extract high-resolution depictions of the group’s structure and participants’ position. Specifically, researchers often leverage network data to produce individual- and network-level variables that might later be leveraged in more traditional regressions. Network variables can be extracted from networks to represent constructs that describe: (a) the position of a single individual within their network, (b)
the immediate ‘community’ of individuals surrounding a focal individual, or (c) the network as a whole. Whereas each of these constructs are mere calculations of nominations, researchers develop operationalizations for what they represent socially or psychologically based on the type of nomination or tie being used.

Perhaps most notably, the number of social connections that one member possesses with other members of their small group is considered centrality. When captured in directed networks where group members nominate others, centrality is distinguished between outdegree centrality (i.e., nominations made) and indegree centrality (i.e., nominations received). Indegree centrality has received substantial attention as a marker of one’s position. For instance, members who received the greatest number of nominations as an advice-giver from other team members had more power and influence within a team (Sparrowe et al., 2001). Whereas degree centrality represents the mere ‘count’ of nominations or ties with others, it is also computed into many varying centrality indices that target specific dimensions of one’s position. One example type of centrality focuses upon the extent that an individual falls along the chain ‘between’ other nodes (i.e., betweenness centrality). One such variant of centrality that will be relevant for my thesis is eigenvector centrality, which is an approach to re-weight the number or strength of nominations based on the nominations received by neighbors in the network. When applied with nominations based on interactions or affiliative ties between members, eigenvector centrality represents an individuals’ embeddedness in the social affiliations within the network; a high volume of connections alongside nominations for from others receiving many nominations.

**Personality and Structural Positions within Networks**

Beyond examining social structures for their own sake, it is crucial that we understand how personal characteristics and team composition shapes these structures. Emerging research
points toward the existence of individual differences regarding social relationships in groups.

People differ in their propensity to both pursue structural positions in groups and in their propensity to form relationships. Personality measures are, indeed, powerful tools for understanding how individuals develop relationships with others and position themselves within groups because they shape status pursuit motives and the ways that people present themselves to others (Anderson et al., 2001). When considering the dispositional or personality facets that may predict where people are situated within group networks, I consider two theoretical frameworks. The first of which focuses on the volitional or self-regulated process of how we ‘curate’ our connections with others, whilst the second more broadly focuses on predicting how personality influences dominant social behaviours in less-volitional ways.

Volitional or self-regulated theories often leverage the assumption that humans are inherently social creatures that have a fundamental need for superiority or status (Adler, 1930). Studies examining extraversion demonstrate this self-regulating function of personality facets. *Extraversion* refers to the extent to which an individual tends to be outgoing, active, assertive, and enthusiastic (McCrae & John, 1992). Longitudinal research by Anderson and colleagues (2001) examined how differences in personality traits can predict status pursuit behaviours in groups. Extraversion was a particular trait that predicted status in small groups with time. The authors theorized that this trait predicted the extent that status was rewarding and predicted status pursuit (e.g., social activity, assertive behaviors, tactics to get ahead). Additional research using social network analysis has also demonstrated how extraverted individuals deliberately engage in certain network-enhancing actions, but otherwise do not have indiscriminately more-connected networks. For example, undergraduate students who are extraverted tended to have larger advice-sharing networks but did not differ from less-extraverted individuals in relation to the extent that
their personal ties were connected or their emotional closeness to others (Malcolm et al., 2021). Such research emphasizes how personality traits predict the ways that people orient themselves within a social network.

Social exchange theory can also be applied as another volitional theory to understand the dyadic nature of interactions in social relationships as it can impact how individuals come to perceive others. Social exchange theory focuses on how others perceive the personality of a focal individual. According to this theory, individuals pursue friendships in a self-interested manner, such that they maximise benefits and minimise the cost of such relationships (Cook et al., 2013). Hence, based on the perceived value of a person from a social exchange perspective, an individual’s personality and the associated behaviours that accompany it can play a large role in whether others decide to interact with said person. In line with this thinking, research has found that when selecting for work partners, participants tended to favor those with a reputation for being hardworking, as they stand to benefit from this relationship through work-related advice (Hinds, Carley Krackhardt & Wholey, 2000).

A further distinction when considering ‘why’ personality predicts network position is the extent that network position is driven by the mere dominant response and disposition of individuals, aside from their motives for status or influence. Cao and Smith (2021) identify how sociological research emphasized the self-organizing nature of groups (i.e., structure-centric approach). Taken from this perspective, individual differences may have a direct influence on positions in a social network through less-agentic means (i.e., extraverts interact with more people) alongside indirect influences through the goals and motives emphasized by theories focused on self-regulation and social exchange. As such, my thesis will work on the assumption that groups entail processes that may tend to sort people with certain dispositions into more or
less central positions, whilst a group’s structure is also shaped by individuals’ agency in pursuing and maintaining relationships as well as structural positions.

**Empirical findings**

Despite competing theoretical stances for why personality relates to one’s position within groups, researchers in social and organizational psychology are incrementally developing an empirical evidence base to understand how personality traits and dispositions predict network position. As the most expansive review of literature to date, Fang and colleagues (2015) summarised 138 studies in which personality trait measures were quantitatively used as predictors of indegree centrality and brokerage (i.e., being in a position between two unconnected nodes) within both expressive and instrumental networks. Expressive networks often refer to social ties related to socioemotional support and normative expectations, whereas instrumental networks refer to ties related to gaining resources and information for instrumental purposes (Podolny & Baron, 1997). This review more specifically included studies involving two approaches to study associations between personality and network position: (a) whole-network design in which participants nominate others in their organization (120 effects) or (b) ego network designs, in which each participants’ networks are based solely on each participants’ self-reported number of alters, and the extent to which the participant reported connections between alters (7 effects).

Table 1 highlights the meta-analytic findings reported by Fang and colleagues (2015) who broadly revealed that personality predicted job performance and career success above and beyond network position, and that network position partially mediated these effects. Effects varied as a result of the specific trait under investigation, and I will characterize the evidence
pertaining to the three most commonly-studied traits: a) extraversion, b) conscientiousness and c) agreeableness.

**Table 1**

*Meta-analytic Aggregated Effects of Personality on Network position (Adapted from Fang et al., 2015).*

<table>
<thead>
<tr>
<th>Trait</th>
<th>Network-derived Structural Position</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Indegree Centrality</td>
<td>Brokerage</td>
</tr>
<tr>
<td>Extraversion</td>
<td></td>
<td>0.05</td>
<td>-0.02</td>
</tr>
<tr>
<td>Openness to experience</td>
<td></td>
<td>-0.10</td>
<td>0.09</td>
</tr>
<tr>
<td>Conscientiousness</td>
<td></td>
<td>0.02</td>
<td>0.06</td>
</tr>
<tr>
<td>Agreeableness</td>
<td></td>
<td>0.04</td>
<td>-0.01</td>
</tr>
<tr>
<td>Neuroticism</td>
<td></td>
<td>-0.05</td>
<td>0.02</td>
</tr>
</tbody>
</table>

*Note. Fang and colleagues examined studies considering the association between personality traits and both indegree centrality (i.e., mere number of nominations one receives in organization) as well as brokerage (i.e., the extent that an individual was connected with two individuals who were otherwise not connected). Bolded meta-analytic effect sizes were significant (p < .0005).*

Extraverted individuals are sensitive to reward signals and seek stimulation through social interaction. One might assume that such tendencies would result in a larger friendship and advice networks. However, Fang and colleagues (2015) reported no significant relationship between extraversion and indegree centrality. Conceptually, the authors linked these findings to evidence involving leadership in which extraverts gain status early-on and are the first to ‘rise’ into leadership positions before suffering from a decline in perceived status (Bendersky & Shah, 2013). Meanwhile, Fang and colleagues reported a positive relationship between extraversion
and the likelihood that a node holds a brokerage position within a social network. This was interpreted through extraverts’ tendency to bring their different social contacts together, therefore being a hub that connects others who would otherwise not be linked.

*Conscientiousness* reflects the extent to which an individual is hardworking, organised, persistent, and detail oriented (McCrae & John, 1992). Although this personality trait was unrelated to interpersonal networks, employees high in conscientiousness may hold brokerage roles due to people’s preference for work partners who are hardworking and capable (Hinds et al., 2000). In line with this thinking, Fang and colleagues (2015) found that conscientiousness positively related to brokerage. The authors linked this finding to evidence suggesting that coworkers often seek conscientious people for work related advice and information, who can than also act as a work-related information bridge between different social cliques. Interestingly, they further found it to be positively related to indegree centrality in instrumental networks despite previous research suggesting otherwise.

*Agreeableness* characterises an individual who is cooperative, kind, and trusting (McCrae & John, 1992). With a motivation to develop positive relationships with others (Nettle, 2006) and help integrate different people’s views and needs (Jensen-Campbell et al., 2003), one might believe that agreeable people would be selected more as friendship partners and have high indegree centrality. However, Fang et al. reported that agreeableness was unrelated to centrality, whilst being related to brokerage. The insignificant relationship with indegree centrality could be explained by research suggesting that when encounters are too brief, superficial or indirect, the positive effects of agreeableness is undetectable (Doroszuk, Kupis, & Czarna, 2019). Perhaps in large organizational networks, agreeableness effects are hesitant to emerge compared to small group environments.
In sum, certain personality traits may dispose or motivate people to situate themselves into advantageous positions (centrality, brokerage) within their networks that link members based on friendship, sharing advice, or being interdependent. Despite that, it is notable that one network construct broadly reflecting the number of nominations from other network members (i.e., centrality) was not significantly related to three traits that theorists expect to produce positive tendencies toward social interaction or motives to connect with others. The variability in these associations may be explained via several gaps in the evidence base. First, articles documented by Fang and colleagues included large-scale, whole-network designs (e.g., studies of a single network including hundreds of individuals) or ego network designs (e.g., surveys where each individual reports their own, personal, network). Whole-network designs included mainly larger-scale networks encompassing entire organizations that involve distinct network processes from those that are enacted in small groups. For instance, a personality trait such as agreeableness may be more salient in smaller groups where members can each form unique relationships. Large-scale designs also limit the potential to uncover between-network heterogeneity. Studies with small groups are therefore needed.

A further gap involves a need to target more specific individual difference variables. Despite its popularity in the literature, the Big-5 has been criticized because of the breadth of the personality domains, in which each trait represents numerous underlying facets. For instance, research within the leadership literature has shown that analysing HEXACO personality at the facet level can yield different relationships when compared to analyses at the domain level (Karlsen & Langvik, 2021; Kornør & Nordvik, 2004). Furthermore, research suggests that domain-specific individual differences beyond that of the Big-5 personality traits can account for variance in peoples’ propensity to connect with others in the workplace (Totterdell, Holman, &
Hukin, 2008). When applied to a network approach, one can apply the same argument that specific personality facets can explain unique variance in the network criteria. Lastly, it should be noted that the studies covered in Fang and colleagues (2015) review mostly utilised indegree centrality – raw number of nominations from others. As such, there exists a gap wherein researchers are not controlling or considering the impact of group structure in their analysis of how individuals come to position themselves in their groups.

My thesis fills these gaps involving the need for small groups research alongside specific personality traits or facets as predictors, by proposing that dispositional positive affectivity can impact one’s position within small group social networks whilst utilising network constructs that account for group structure.

**Positive Affectivity and Socialization**

Positive affectivity reflects stable individual differences in the extent to which an individual experiences positive emotion; and as a consequence, how they interact with others and with their surroundings. People with high positive affectivity are typically enthusiastic, energetic, confident, active, and alert (Watson & Naragon, 2009). In relation to the Big-5 traits, positive affectivity is positively correlated to extraversion, agreeableness, conscientiousness, and openness to experience, and negatively correlated to neuroticism (Watson & Naragon, 2009). Unlike the domains of the Big-5, positive affectivity is comparatively more narrowly oriented towards members’ observed social disposition. Positive affectivity at a dispositional level also has a direct manifestation at a momentary level, being variable over the course of the day. Research on positive affectivity has demonstrated its importance regarding mental and physical health. For instance, low levels of positive affectivity are a symptom of mood disorders including depression or anxiety. In addition, physical health (e.g., increased resistance to infectious
diseases) coupled with marital and job satisfaction can be predicted by past measurement of positive affectivity (Watson & Naragon, 2009). As a disposition that is linked to how an individual feels and presents themselves to others, research into positive affectivity has also focused on how it can impact the way an individual socialises. For instance, whereas low positive affect produces feelings of being unsocial and lacking energy, positive emotions often result in people feeling more sociable and energized (Diener et al., 2015).

Researchers have emphasized how people with high positive affectivity perceive more expansive networks, tend to behave in a more prosocial manner, and develop stronger relationships. In younger individuals, those with higher life satisfaction, a construct closely related to positive affect (Singh & Jha, 2008), often report having more close friends (Kang, 2023). Positive affect can also motivate an individual to act on those feelings of being social. For instance, research suggests that high positive affect in early adolescence predicted lower levels of conflict in friendships that occur in younger adulthood (Kansky, Allen, & Diener, 2016). Positive mood of employees has also been associated with helpful workplace behaviours and extra-role actions (George, 1991), suggesting that the benefits of positive affect in promoting prosocial behaviour can also be found within the workplace. Lastly, higher positive affectivity has been found to be associated with more substantive interactions when first meeting others such that the other party perceives a larger self-other overlap within new friendships (Berry & Hansen, 1996). Such studies reveal how those who typically experience positive moods are likely to seek and maintain new friendships that could have long-term positive consequences.

Whereas positive affectively was not documented as a common disposition in reviews on social position in organizations (e.g., Fang et al., 2015), several existing influential social network studies have focused on positive affect and related constructs (e.g., mood, subjective
wellbeing) at a whole-network level to understand how positive dispositions and relationships co-evolve. Using data from the Framingham heart study – tracking members of a single community over decades – Fowler and Christakis (2008) found that individuals with higher levels of subjective well-being in a social network were more likely to be clustered together and be associated with one another. Using a wellbeing measure that resembles common tools for measuring positive and negative affect, the researchers speculated that this was due to three primary processes: 1) induction, positive emotions of one person causes another to feel the same; 2) homophily, the tendency to relate to others with similar affectivity; or 3) confounding through a shared context (e.g., individuals experience the same social context, which independently influences wellbeing). Fowler & Christakis (2008) demonstrated that subjective wellbeing (and in a sense, positive affectivity) can function on a dyadic level that structures ties and can be a source of social influence.

Taking existing empirical research in aggregate, positive affectivity is a disposition that often leads individuals to pursue new or diverse friendships, and to maintain those friendships with time. Despite the abundance of research showing the social consequences of positive affectivity (see Moore et al., 2018), there remains a lack of research testing specific mechanisms of positive affectivity on friendships and relationships. Much of the research studying affectivity in groups stems from single-source correlational research (i.e., examining how self-report positive affectivity relates to self-reports of connections with others). From a network perspective, existing empirical research has surmised mechanisms explaining the link between positive affectivity and network position, however no research documents how positive affectivity as a disposition shape can shape how people are situated within small groups.
The Current Study

The current study examines how personal characteristics (i.e., tendency for one to experience positive emotions) and team composition come to shape social network position. My thesis focuses on college student clubs and teams as small groups, because they are an important social context in members’ lives that also feature core characteristics of small groups (e.g., shared goal; social structure). Regarding the forms of nominations used to generate networks, my thesis examined both (a) interpersonal interaction networks, involving interactions outside of the group context, and (b) status nominations.

Each type of network produces unique individual and group-level variables that I operationalize in contrasting ways, as articulated within Table 2. As the first type of network in this thesis, nominations for interactions with other members outside of the primary group setting are useful because they reflect relatively concrete actions (e.g., spending time together or communicating outside of the primary group environment). Centrality in this network is a highly descriptive sociometric measure known as eigenvector centrality and reflects one’s embeddedness in the social and affiliative ties between members, whereas density reflects interpersonal connectedness in the group as a whole. My second network was derived from status nominations that involve conferred respect, admiration, and voluntary deference (Anderson et al., 2015). Reputational status, the form addressed using nominations in the present investigation, reflects one’s relative position within the group status hierarchy, and includes the respect, admiration, and voluntary deference group members afford to the focal individual. Operationalizing networks emanating from status nominations is a relatively direct task: Centrality indicates reputational status. Whereas density is less meaningful with such nominations, group-level network centralization can be used to represent the extent to which there is high variability in status nominations.
received (i.e., certain members receiving disproportionate number of nominations relative to others). The decision to integrate a status network stems from the individuals’ fundamental need for status attainment (Adler, 1930) and the volitional nature of status pursuit where individuals invest and use resources in return for social standings (Lin, 1999).
Table 2

*Relevant Network Variables Leveraged in This Research.*

<table>
<thead>
<tr>
<th>Level of analysis</th>
<th>Network construct</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Individual level (interaction ties)</strong></td>
<td>Eigenvector Centrality</td>
</tr>
<tr>
<td></td>
<td><em>Embeddedness within affiliations and interactions of peers</em></td>
</tr>
<tr>
<td></td>
<td>Computation: Accounts for the quantity of nominations from others (i.e., degree), and the ‘quality’ of those nominations (i.e., degree of neighbors). Eigenvector centrality is computed by awarding individuals with a power score (i.e., 1), and then iteratively adjusting that value based on the power of neighbors. Resulting value ranges from 0 to 1.</td>
</tr>
<tr>
<td></td>
<td>Theorized link with positive affectivity: People with high positive affectivity gain central positions.</td>
</tr>
<tr>
<td><strong>Group level (interaction ties)</strong></td>
<td>Density</td>
</tr>
<tr>
<td></td>
<td><em>Relative connectedness among group members</em></td>
</tr>
<tr>
<td></td>
<td>Computation: Number of observed nominations, divided by the maximum number of possible nominations.</td>
</tr>
<tr>
<td></td>
<td>Theorized link with positive affectivity: Groups with higher average positive affectivity will be denser, as members are more likely to be connected to one another.</td>
</tr>
<tr>
<td><strong>Individual level (status)</strong></td>
<td>Indegree centrality</td>
</tr>
<tr>
<td></td>
<td><em>Reputational status in group</em></td>
</tr>
<tr>
<td></td>
<td>Computation: Raw number of incoming nominations from other nodes.</td>
</tr>
<tr>
<td></td>
<td>Theorized link with positive affectivity: People with high positive affectivity will be perceived as having more status.</td>
</tr>
<tr>
<td><strong>Group level (status)</strong></td>
<td>Centralization</td>
</tr>
<tr>
<td></td>
<td><em>Concentrated status distribution (versus a network in which status nominations are distributed equally among all members).</em></td>
</tr>
<tr>
<td></td>
<td>Computation: Difference between the centrality score of the most central actor and those of all other actors (i.e., variability in nominations received). The simplest formula is to use the sum of differences in individual degree centrality scores divided by the maximum possible sum of differences in each group (i.e., one calculation of centralization would be to examine the standard deviation of centrality values for all members in the group).</td>
</tr>
<tr>
<td></td>
<td>Theorized link with positive affectivity: Groups that have higher average positive affectivity will have less variance on who has status in the group. [Exploratory]</td>
</tr>
</tbody>
</table>
In sum, with the assumption that these two networks involve different pathways toward being central within a group, I integrated interaction network nominations to reflect affiliative, concrete, and relational group networks reflecting interpersonal connectedness among members and one’s embeddedness in group. I integrated status nominations to target the social position that members are conferred as well as how centralized the network is with respect to status as a result. Past research reflects how personality traits relating to sociability relate to some – but not all – markers of network position (e.g., Malcolm et al., 2021). As such, I was interested in examining the extent that positive affectivity related to network processes relating both to interaction in groups and with the distribution and conferral of status.

**Predicting individual structural position using personal characteristics**

Based on past literature demonstrating the positive social outcomes associated with positive affect, I believe that individuals who possess high levels of dispositional positive affectivity will be more likely to find themselves in the ‘center’ of their relational ties for interaction networks. Furthermore, this tendency for these individuals to embed themselves into positions of influence through their connections with other people is best represented through the network construct of eigenvector centrality.

**H1a: Positive affectivity will be positively associated with eigenvector centrality in out-of-group interaction networks.**

In regard to status, research has repeatedly demonstrated that high status employees tend to have larger and more expansive social networks (Brashears, 2011; Smith et al. 2012; Wasserman & Faust, 1994), and that this can be attributed to differences in how employees perceive the importance of status coupling and social relations/networks (Cao & Smith, 2021). For clarity purposes, the current research will focus on reputational status (hereby referred to as
simply status). Taken together, I anticipate that those with high positive affect will be nominated into higher status positions.

\textbf{H1b: Positive affectivity will be positively associated with a greater number of reputational status nominations.}

\textit{Predicting Group Structure}

The proposed thesis will also focus on how the dispositional tendency to experience positive emotions relates to group network structure. My thesis will examine the extent to which small groups’ aggregate positive affectivity is accounted-for based on between-network structural differences (e.g., density). The decision to have each network’s positive affectivity as a compositional variable is due to nature of the data. Specifically, I am working with the distribution of relations among actors in a network (i.e., status, friendship). As such, I chose to aggregate individual club members’ positive affectivity to the group-level to represent each network’s overall/mean positive affectivity. For interaction networks, I expected that club aggregated positive affect would relate to the interconnectedness of interaction ties of the club itself. This is based on past affectivity research suggesting that positive individuals are likely to have larger and more diverse friend groups (Feiler & Kleinbaum, 2015). Thus, one could argue that a group that is homogenous in its positive affectivity will likely be more tight-knit and interconnected as a whole.

\textbf{H2a: Group mean positive affectivity will be positively related to group density in out-of-group interaction networks.}

For status networks, I expect that the high connectedness of groups with higher positive affectivity might (also) lead to more consistent status nominations toward focal members (i.e., centralization). I acknowledge that positive affectivity may certainly relate integration among
members and by extent less hierarchical relations in groups. However, I operationalized status in terms of the reputational status targeted toward a maximum of five group members (see measure, below); as such, positive affectivity was expected to produce less variability among members regarding who was nominated as being a high status member. This hypothesis is not substantiated by theory and is exploratory in nature.

**H2b:** Group mean positive affectivity will be positively related to centralization in reputational status nominations.

**Group Context Interacts with Individual-level Association**

My proposed thesis will also explore the extent that group context shapes the link between one’s disposition and their network position. Specifically, I will explore the extent to which average positive affectivity amongst members of a group moderates the relationship between an individual member’s positive affectivity and their tendency to be perceived as having high status by occupying a central position.

As there is contrasting theory within the literature for how group contexts can moderate the relationship between disposition and network position, I did not form hypotheses about the specific nature of this interaction. I did expect a cross-level interaction because of two lines of thought. First, prominence or observability of one individual’s affect is likely evident to the extent that they differ from others in their group. From this observability perspective, one possibility is that the association between positive affectivity and centrality or status is stronger when the group average positive affectivity is lower. Second, a competing line of thought is that members gain status and centrality by being representative of the group. This representativeness perspective means that perhaps the association between positive affectivity and centrality is relatively stronger when the group average positive affectivity is higher. Because both of these
competing arguments (observability and representativeness) are plausible, I did not form hypotheses for this question.

Method

Participants

Participants were members from various university student clubs ($k = 16$) from a large university in Canada. Inclusion criteria for involvement primarily focused on the group level, and aligned with common definitions of small groups (i.e., Kozlowski & Ilgen, 2006) focusing on group member interaction, social structure, and member interdependence. My specific criteria included: a) a small to moderate club size, which permitted member interaction (i.e., no larger than 150 members), b) occurrence of club activities, demanding at least biweekly member interaction (i.e., clubs included must hold at least biweekly meetings or events), and c) presence of shared goal or task uniting members (e.g., members must share some form of task or outcome interdependence).

Numerous types of clubs were represented in this sample, including: (a) hobby clubs, where members met weekly or biweekly within a structured environment to engage in key activities like snowboarding or dance (41%), (b) club level sport teams where members practiced numerous times weekly and participated in regional competitions as a team or club (e.g., Women’s football team; Taekwondo club; 22%), (c) student clubs including an administrative team responsible for organizing events to unite students with shared professional interests or for philanthropic outcomes (e.g., future black lawyers; vegan society; 9%), (d) clubs meeting monthly to organize events celebrating culture (e.g., Japanese Students’ Association; 19%); and (e) student governments (9%). The mean group size was 33.4 members ($SD = 22.23$) ranging from 9 to 62. Although the clubs that participated in the studied were varied in their activities, all clubs demonstrated a sense of
connectedness and shared goals amongst members that met my definition of what constitutes a small group.

Regarding individual characteristics, 262 members comprised my sample. Participants’ average age was 19.9 (SD = 1.88) and ranged in tenure within the university (i.e., 19% freshman, 28% sophomores, 29% juniors, 17% seniors, and 7% graduate students). All participants provided informed consent and ethical approval was obtained from the institutional review board prior to recruitment.

**Figure 1**

*Flow Chart of Club Participation and Data*

![Flow Chart Image]

**Procedure**

All clubs were comprised of both existing members from previous years and new members in their first academic year with the club. Club recruitment meetings took place during October and November, which represented the second or third month of membership for new club members. Therefore, data was collected at a timepoint in which membership had stabilized.
and when newcomers had opportunities to connect with other members. Clubs that showed interest at this stage of recruitment were contacted via email and told of the study purpose and what club members would be expected to do during the study. When club presidents provided permission, researchers attended an in-person club meeting and invited club members to take part in the study using electronic tablets or participants’ smart phones. As incentive for taking part in the study, participants received a $5 gift card to Tim Hortons for completion of the survey.

**Measures**

**Peer Interaction Nominations**

Participants’ nominations of social ties were measured to produce networks (Appendix A), from which crucial network constructs could be derived. Participants completed a name generator peer nomination item wherein they were asked to list up to ten complete names of club members that they often spend time with outside of club activities, using the prompt: “*In the spaces below, please list the names (max 10) of club members whom you have spent time with, outside of club activities, at least once in the past several months.*” Such sociometric items that focus on more concrete forms of interaction – as opposed to asking participants to identify ‘friends’ – are often used in educational psychology to construct classroom networks (e.g., Serdiouk et al., 2016).

On a subsequent survey page, participants were also prompted to rate the intensity of their interactions with peers allowing for the creation of weighted nomination. Participants were provided with a prompt, “*For each name, please rate how frequently you spend time together, away from club activities.*” Participants were then requested to indicate frequency of interactions in the past 30 days with scaling response options that included ‘every day’, ‘once a week’, ‘once
or twice’, and ‘never’. This assessment of peer interaction intensity was not integrated within the present analyses because my focus was on calculating networks using unweighted nominations regardless of the strength of relationships.

Peer Status Nominations

To create a peer status network, a similar methodology as above was applied (Appendix B), but instead participants were asked “In the spaces below, please list the names (max 5) of club members that you believe are respected, admired, and show competence when it comes to club activities.” Participants were provided space to list up to five individuals. As characterized by Xu, Benson, and Evans (Under Review), this assessment of status represents a reputational peer nomination that is absolute in nature. The measure is reputational because respondents reported their sense for individuals’ status in the group as a whole as opposed to reporting their own relationship with peers. Compared to items that are clearly zero-sum in nature (i.e., ranking participants hierarchically), this peer nomination approach is an absolute measure.

Positive Affectivity

Individual club members’ level of positive affectivity was measured using Ripper and colleagues’ (2018) emotional reactivity, intensity, and preservation (ERIPS) scale (totalling 60 items; Appendix C). This scale presents participants with the original 20 adjectives of the PANAS scale that assess positive and negative affect, with adaptations to the instructions and response scales to reflect reactivity, intensity, and preservation. My analyses focus exclusively on the reactivity subscale (20 items), and I excluded items pertaining to intensity and preservation subscales from analyses (See Appendix E for explanation). Participants were asked “When exposed to a situation that would make the ‘average’ person experience this feeling, how likely is it that you will experience this particular feeling?” (1 = not at all likely; 5 = extremely
likely). This scale is interpreted similarly to the original PANAS, but focuses respondents on their beliefs about their prevailing responses to events relative to a typical person.

**Demographics**

Participants were also asked to complete demographic items (e.g., age, gender, year of study, and ethnicity) along with items regarding participants’ position within clubs and tenure (Appendix D).

**Analyses**

Initial steps for analyses involved managing the peer nominations as networked data. This involved first managing missing data or incomplete responses, and coding responses to descriptive or categorical items. For instance, using participant self-report of their task-related roles within their club, I classified each participant within an authority role variable to reflect participants in a formal leadership or management position (1; president, vice-president, coordinator of key club function) or in no leadership or management position (0). These initial steps were followed by network analyses and multilevel analyses.

**Constructing Networks and Extracting Network Variables**

Network analyses entailed constructing the club-specific data structure to model participant networks based on peer nominations, and then extracting network-related variables. To create the data structure, an edge list with reported ties were created for each student club using MS Excel. This involved a list array of all outgoing nominations of each team member separated, wherein each nomination occupied a single row. For network data, missing data is important to address prior to analysis. For instance, when club members were absent or did not complete a survey, their missing data results in missing data for all others whom they may have nominated (i.e., disrupting centrality values) as well as missing data from the group-level
network (i.e., disrupting density or centralization values). Past network research has demonstrated that even small numbers of missing nominations in a network can lead to severe bias in the data, and one common rule of thumb is that missing more than 30% of peer nominations in a network can produce bias (e.g., Borgatti, Everett, & Johnson, 2013; Kossinets, 2006). This research indicates both the value of gathering complete networks, and carefully considering approaches to impute missing nominations.

More recent simulation research has provided a more positive perspective of missing data in small sized, centralized networks with ‘directed’ nomination data. Indeed, Smith et al. (2022) simulated bias emanating from varying proportions and with differing imputation decisions and revealed relatively low levels of bias in centrality variables with up to 40% of missing nominations, even when foregoing any imputation of missing responses. The authors indicated that simpler imputation methods – or non-imputation – was especially suitable for degree-based centrality measures like those from this study, and for density/centralization variables. One important caveat to this message is that bias increases substantially when highly nominated participants do not complete network surveys.

After preparing network matrices and managing missing responses, the subsequent step involved using statistical programs (Gephi and UCINET) to extract individual- and group-level network variables to be used within regression models. GEPHI was utilised to calculate individual-level centrality variables like eigenvector and indegree. Density of an individual network was calculated by dividing the total number of observed connections with the maximum number of possible connections. Centralization was calculated by dividing the sum of calculated differences in individual degree centrality scored by the maximum possible sum of differences in each group.
Multilevel Analyses

Pertaining to the multilevel models, recall that we expected that eigenvector centrality and number of status nominations would be uniquely predicted by positive affectivity, for the interaction and status networks respectively. I also sought to probe cross-level interactions examining group-level affectivity moderating individual-level associations. To test my hypotheses, I focused on a model-building approach within MPlus (Muthén & Muthén, 2017) that involved: (a) constructing random-intercept models featuring several key control contextual and individual variables (Model 1), (b) integrating focal predictors (Model 2), and (c) integrating cross-level interactions (Model 3). Model 1 included control variables that were primarily demographic or contextual (i.e., age, sex, ethnicity, authority position) and were chosen based on their potential relationship to how individuals interact with others in small groups. For instance, authority positions within a club (e.g., club presidents) was expected to be an important contextual predictor of an individual within networks. Following this null model, I included random-intercept models that included the focal predictors (affectivity) at within- and between-levels (Model 2). The final, random slopes, model introduced random slopes for the within-level association between positive affectivity and centrality, and then introduced group-level positive affectivity as a predictor for the slope of this individual association. This means that models were fit hierarchically to test relative contributions of positive affectivity, first allowing variability in team intercepts only (Model 2) and then allowing random variability in team slopes (Model 3) to test for cross-level interaction. This approach was guided by recommendations for the conduct of multilevel regressions, involving both methodological guidance (Aguinis et al., 2013) and the practical recommendations from Sommet and Morselli (2021).
Regarding the selection of modelling procedures, both interaction and status network utilised maximum likelihood (ML) estimation – a statistical method in which observed data is used to estimate the parameters of the probability distribution that generated the sample. The models differed, however, when specifying the distribution of the dependent variable. Specifically, even though ML estimation is often robust to non-normality, status nominations represented a count variable and demonstrated properties of a Poisson distribution ($M = 2.43$, $SD = 2.60$, $Range\ 0\-32$) with skewness of 4.47 and kurtosis of 26.10. This nonnormal distribution can be explained by the binary, count nature of nominations, along with the unequal distribution of nominations among members. Eigenvector centrality nominations were computed and weighted based on nominator centrality; it was not a count variable and was distributed among members. As such, for the status network I specified a Poisson distribution in Mplus (i.e., see relevant code within Appendix F: COUNT ARE (p)). Furthermore, my choice of statistical software for conducting multi-level modeling, allowed me to assess the pseudo-$R^2$ for the null and random-intercept models on both within and between group levels. Unlike the traditional $R^2$, the pseudo variant is used to estimate proportion of group/individual level variance predicted at each level. This statistic could not be computed for Model 3 (Random Slopes) because the variance of the dependent variable varies as the function of the group-level predictor.

Regarding variable preparation, individual-level variables were centered relative to the group mean, whereas group-level variables were centered relative to the grand-mean. It should be noted that centering of data in multilevel research is a debated topic, with some researchers (see Antonakis et al., 2021) suggesting that the practice of centering within groups for Level 1 predictor variables can be unnecessary in most cases, as it complicates interpretation of marginal predictions and marginal effects. In their paper, Antonakis and colleagues (2021) examine how
cluster-mean centering can produce within effects as Level 1 that are free of endogeneity issues, however the technique has limitations when modeling for Level 2 covariates. They also argue for use of a correlated random effects modeling approach, wherein it is assumed that the random intercepts are uncorrelated with the regressors. Despite their skepticism, the authors do note that cluster-mean centering is recommended when the interest is in estimating the between effects in Level 2 instead of the contextual effects along with the within effects at Level 1. With that in mind, I opted to still cluster-mean center for my Level-1 predictors to establish meaningful interpretation of each variable. This decision was heavily influenced by past recommendations for examining cross-level interaction when using multilevel modeling (Aguinis, Gottfredson, & Culpepper, 2013).

For my analyses I opted to utilise unstandardized beta coefficients in Mplus as I am most concerned about the relationship between affectivity and network positions rather than examining how other variables come to impact affectivity and vice versa.

Results

Characterizing Club Networks

Preliminary analyses involved characterizing the club networks in relation to: (a) the variability in size and nomination patterns, (b) patterns in missing nominations, and (c) illustrative visualizations of network structure. Regarding the description of networks, participants on average received nominations from 2.4 individuals ($SD = 2.8$) and gave out 3.4 nominations of their own ($SD = 2.8$) in relation to the interaction prompt. For the status prompt, participants received an average of 1.6 incoming nominations ($SD = 3.9$) and gave out 2.2 nominations ($SD = 1.9$) of their own. The maximum number of nominations received for participants was 14 for the interaction network, and 32 for status nominations. Considering the
association between nominations received in both networks, the number of nominations indexed via raw indegree centrality was moderately correlated across networks ($r = .59$), indicating that nominations relating to status and interactions were similar but nevertheless distinct. Regarding the correlations between indegree and eigenvector centrality variables in each network, moderate correlations were evident within the interaction network ($r = .78$) and status network ($r = .69$). These correlations are unsurprising as they are each calculated based on the nominations a participant received, but nevertheless demonstrate that there is not complete overlap between the distinct indicators of centrality.

To assess the impact of missingness on resulting networks, Figures 2 and 3 below illustrate the distribution in club participation rate for both interaction and status networks respectively. Participation rate can be difficult to assess because club membership varies throughout the academic year and because ethical concerns prevented me from requesting a complete club roster from club presidents. As such, I estimated participation rates by considering the proportion of nominated individuals who completed surveys over those who were nominated but did not complete the survey. The average participation rate amongst all the clubs was 86% ($SD = 7.0$) for the interaction network and 82% ($SD = 14.7$) for the status network.

To address the important consideration regarding the proportion of highly nominated individuals who were missing (Smith et al., 2022), I calculated the number of total edges (nominations) by the number of participants that were nominated but did not participate in the study (hereby referred to as NBNP). To gauge the ‘importance’ of NBNP ($n = 175$), I compared this group of participants with other participants on key variables. NBNP participants received an average of 1.3 ($SD = 2.3$) status nominations and 3.8 ($SD = 2.8$) interaction nominations, along with an average of 0.2 ($SD = .25$) for eigenvector centrality for interaction nominations.
Following this, I conducted an ANOVA and did not identify a significant difference in the average centrality for NBNP and survey participants (Eigenvector: $F(1,539) = 0.664$, $p = 0.46$; Status: $F(1, 555) = 1.537$, $p = .17$). I also conducted a chi-squared for independence to determine whether the most highly embedded and nominated nodes (+1 SD vs rest) were independent on participant type (took part vs NBNP) for both interaction and status networks respectively. The results were significant for interaction, $\chi^2 (1, N = 557) = 6.63$, $p = .01$, and status network, $\chi^2 (1, N = 557) = 6.21$, $p = .03$. This indicates that highly nominated and important nodes of both networks (interaction: 15.9% for took part, 5.4% for NBNP; status: 5.4% for took part, 2.7% for NBNP) were more likely to have taken part in the study relative to people who did not participate.
Figure 2

*Histogram of Participation Rate of Clubs for Interaction Network*

![Histogram of Participation Rate of Clubs for Interaction Network](image)

Figure 3

*Histogram of Participation Rate of Clubs for Status Network*

![Histogram of Participation Rate of Clubs for Status Network](image)
Figure 4

Two Illustrative Network Graphs of Interaction Networks

Note. This figure illustrates the network visualization for two groups in relation to interaction nominations and was produced using the Gephi software. Each dot on the graph indicates an individual participant of their respective club, with the color of the dot representing the level of eigenvector centrality values for interaction networks. Dots with darker hues indicate nodes (participants) with comparatively higher nominations. For parsimonious reasons, the graphs above are undirected. Group #11 (a - left), depicts one club in which participants made a relatively high number of peer nominations, and with a centralized network structure (total nodes = 50, missing members = 8). Group #8 (b - right) represents a sparser network involving several observable subgroups (total nodes = 76, missing members = 15).
Figure 5

Two Illustrative Network Graphs of Status Networks

a: Club #11

b: Club #8

Note. This figure illustrates the network visualization for of two groups in relation to status nominations

and was produced using the Gephi software. Each dot on the graph indicates an individual participant of their respective club, with the color of the dot representing the level of indegree centrality for status networks. Dots with darker hues indicate nodes (participants) with comparatively higher nominations. For parsimonious reasons, the graphs above are undirected. Group #11 (a - left), depicts one club in which participants had more connections, and more agreement (centralization) on the conferment of status (total nodes = 45, missing members = 4). Group #8 (b - right) represents a much sparser network with fewer members being highly nominated overall, and far less agreement on the conferral of status (total nodes = 42, missing members = 10).
Figure 4 and 5 shows the graphs for the interaction network for two clubs. When looking at the interaction graphs, it would seem apparent that Club #11 (Figure A) has an overall more centralized central cluster of members compared to Club #8 (Figure B). This is reflected in their group density scores of 0.41 and 0.17 respectively. Network graphs are also useful for visualising an individual’s position within their networks, evident in the two circled participants within Figure 4a. The red-circled participant is visually more embedded into the club’s network with 13 nominations and an eigenvector centrality value of .78 – the participant circled in yellow received 3 nominations and had an eigenvector centrality value of .30. The red-circled participant occupies a more embedded position due to their own centrality coupled with their connection with other ‘important’ members compared to the yellow-circled participant.

When looking at the status networks, Club #11 (Figure C) has a larger number of edges (connections) between members compared to Club #8 (Figure D). Those in Club#11 also held consistent beliefs when attributing status, and this observation is supported by their respective centralization scores of 0.67 and 0.36. Figure 5d also identifies two participants to help illustrate the salience of individual centrality within the network. The red-circled participant conferred higher status (16 nominations) compared to the yellow-circled participant who received only six nominations.

**Descriptive Data**

Initial analyses included efforts to examine missingness in non-network data, understand scale structure for validated scales, and to examine the extent to which assumptions for proposed multilevel analyses were met. Little’s (1998) test of missing completely at random (MCAR) were conducted on self-report subscales – confirming missing data at random with the exception of the intensity and preservation subscales of the ERIPS (See Appendix E).
The relative novelty of the reactivity subscale (i.e., validated in Nock, Wedig, Holmberg & Hooley, 2008; Ripper et al., 2018), and the importance for my research question led me to conduct exploratory structural equation (ESEM) modeling for positive and negative affectivity items. ESEM is a flexible alternative that permits specification of subscales while allowing items to load on other factors in addition to that which is specified for the item. ESEM also reduces the misspecification in the measurement mode whilst still retaining many CFA and structural equational modeling (SEM) methodological distinct features, such as providing goodness-of-fit statistics. I specified and conducted ESEM with two factors, positive and negative affect, wherein comparative fit index was found to be 0.91, an RMSEA of 0.059, and TLI of 0.888, all of which suggest a good overall fit. Accordingly, Macdonald’s Omega values were acceptable for both positive affectivity (ω² = .81) and negative affectivity (ω² = 0.89). Therefore, participants’ responses reliably generated distinct predictions of positive and negative affectivity.

When conducting multilevel modeling involving clustered data, one key assumption is that the random components are assumed to be normally distributed. As previously mentioned, a preliminary analysis of the status nomination participants received from the status network was found to violate this assumption and was addressed by specifying a Poisson distribution for the dependent variable in MPLUS. A preliminary analysis of the individual-level predictors used in the study indicated that all variables, with the exception of age, fell within -0.5 to 0.5 skewness level – indicating a normal distribution. Age of participants had a skewness of 1.77 and a kurtosis value of 6.98, suggesting that the distribution was not normally distributed and heavily tailed. Age outliers were not addressed as club members’ age had low variability (i.e., all undergraduate students).
Descriptive statistics and bivariate correlations are displayed in Table 2 and are useful for understanding the context for this study and associations between constructs. Initial intraclass correlations revealed that between-team variability accounted for 12% and 17% of the variance for eigenvector centrality and number of nominations received by an individual respectively. Participants’ mean age was 20, with a range of 17-29. Interestingly, positive and negative affectivity were found to positively correlate. For group-aggregated affectivity levels, clubs’ overall positive and negative affectivity ranged from 3.4 to 4.2 and 2.2 to 3.2 respectively, with clubs reporting an average of 3.7 for positive affectivity and 2.6 for negative affectivity. Similar to the individual-level affectivity, both group-aggregated forms were found to be significantly positively correlated. Group positive affectivity did not correlate significantly with a club’s overall interaction network density. Interestingly however, it was significantly correlated with a club’s centralization for status networks.


Table 3

Bivariate Correlations and Descriptive Statistics for Within and Between-level Study Variables

<table>
<thead>
<tr>
<th>Variable</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>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Individually-variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. Indegree (Interaction)</td>
<td>-</td>
<td>(.12)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2. Indegree (Status)</td>
<td>.59**</td>
<td>-</td>
<td>(.17)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3. Eigenvector (Interaction)</td>
<td>.78**</td>
<td>.51**</td>
<td>-</td>
<td>(.12)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. Eigenvector (Status)</td>
<td>.43**</td>
<td>.69**</td>
<td>.58**</td>
<td>-</td>
<td>(.09)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5. Age</td>
<td>.13**</td>
<td>.21**</td>
<td>-.16*</td>
<td>.15**</td>
<td>-</td>
<td>(.11)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6. PA (Reactivity)</td>
<td>.23**</td>
<td>.18**</td>
<td>.20**</td>
<td>.13*</td>
<td>.01</td>
<td>-</td>
<td>(.30)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7. NA (Reactivity)</td>
<td>-.01</td>
<td>.05</td>
<td>-.06</td>
<td>-.05</td>
<td>-.004</td>
<td>.16**</td>
<td>-</td>
<td>(.45)</td>
<td></td>
<td></td>
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</tr>
<tr>
<td><strong>Group-level variables</strong></td>
<td></td>
<td></td>
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<td></td>
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<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>8. PA (Group)</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>9. NA (Group)</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-.71**</td>
<td>-</td>
</tr>
<tr>
<td>10. Status Centralization</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>.26**</td>
<td>.12**</td>
</tr>
<tr>
<td>11. Interaction Density</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>.06</td>
<td>.08</td>
<td>.21**</td>
</tr>
<tr>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>M (SD)</td>
<td>2.4</td>
<td>(2.60)</td>
<td>.155</td>
<td>(3.50)</td>
<td>.22</td>
<td>(2.28)</td>
<td>.13</td>
<td>(2.66)</td>
<td>20.0</td>
<td>(1.4)</td>
<td>3.74</td>
</tr>
<tr>
<td>Range</td>
<td>0-1</td>
<td>0.32</td>
<td>0-1</td>
<td>0-1</td>
<td>17-29</td>
<td>0-5</td>
<td>0-5</td>
<td>3.4</td>
<td>4.2</td>
<td>2.2</td>
<td>0.2-</td>
</tr>
</tbody>
</table>

***p<.001, ** p<.01, * p<.05

Note. ICC values are depicted along the diagonal of the table. Peer nominations were highly kurtotic (κ = 3.15, SE = .21) as expected for a count variable.
**Multilevel Models**

Full results of the interaction networks and status networks are depicted within Tables 3 and 4 respectively. Prior to characterizing key results from the multilevel regressions, an initial note is that fit statistics (i.e., \(-2 \text{ Loglikelihood}\)) for the nested models improved from Models 1 through 3 for both networks.

**Predicting Interaction Network Eigenvector Centrality**

For the interaction network (Table 3), participant age, sex, ethnicity, position in club were entered in Model 1 at a within-group level. In addition, a club’s group density was entered at this stage as well as a between-group covariate. In Model 2, individual level of affectivity, both positive and negative, was added as a within-group predictor as well as a between-group predictor. Pertaining to the cross-level interaction, Model 3 revealed that group-aggregated positive affectivity (between-level) did not predict variability in team-level slope between individual positive affectivity (within-level) and eigenvector centrality \((B = -.00, 95\% \text{CI}[-.357, .350], p = .984)\). For the within-group covariates, age \((B = .06, 95\% \text{CI} [.023, .095], p < .001)\) and position in a club \((B = -.07, 95\% \text{CI}[-.094, -.045], p < .001)\) were found to significantly predict eigenvector centrality, whereas sex and ethnicity were not \((B = .02, 95\% \text{CI}[-.051, .097], p = .55; B = -.07, 95\% \text{CI}[-.094, .045], p = .86)\). Group density of a club was also found to be significant \((B = .88, 95\% \text{CI} [.113, 1.655], p < .05)\). Participants’ eigenvector centrality and overall importance within their group were higher when they were relatively older than teammates, when they held an authority position in a club, and when the club itself was interpersonally very close. Regarding affectivity, results suggest that individual positive affectivity was found to be significant \((B = .09, 95\% \text{CI} [.002, .169], p < .05)\), whereas negative affectivity was not \((B = -.03, 95\% \text{CI}[-.072, .006], p = .097)\). For the group-level predictors, both
positive and negative affectivity failed to significantly predict eigenvector centrality ($B = .17, 95\% \text{CI}[-.055, .432], p = 0.22; B = -.05, 95\% \text{CI}[-.22, .311], p = 0.74$). In other words, participants were likely to have more eigenvector centrality within their tight-knit group regardless of their groups overall affectivity when they themselves were likely to experience positive emotions on a regular basis.
Table 4

Multilevel Regression Models (w/ ML) Predicting Eigenvector Centrality for Interaction Nominations

<table>
<thead>
<tr>
<th>Level 1 (Within group)</th>
<th>Step 1 [random intercept]</th>
<th>Step 2 [random intercept, including affectivity]</th>
<th>Step 3 [random slope, cross-level interaction]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept / Constant</td>
<td>.57 [.072, 1.064] *</td>
<td>.55 [.056, 1.037]*</td>
<td>.51 [-.009, 1.016]**</td>
</tr>
<tr>
<td>Positive affectivity (CWG)</td>
<td>-</td>
<td>.08 [.020, .143]**</td>
<td>.09 [.002, .169]*</td>
</tr>
<tr>
<td>Negative affectivity (CWG)</td>
<td>-</td>
<td>-.03 [-.020, .143]</td>
<td>-.03 [-.072, .006]</td>
</tr>
<tr>
<td>Age (CWG)</td>
<td>.06 [.022, .094]***</td>
<td>.06 [.022, .094]**</td>
<td>.06 [.023, .095]***</td>
</tr>
<tr>
<td>Sex (1, 2)</td>
<td>.05 [-.023, .118]</td>
<td>.03 [-.049, .099]</td>
<td>.02 [-.051, .097]</td>
</tr>
<tr>
<td>Authority role (0,1)</td>
<td>-.08 [-.099, -.051]***</td>
<td>-.07 [-.094, -.045]***</td>
<td>-.07 [-.094, -.045]***</td>
</tr>
<tr>
<td>Ethnicity (1, 2)</td>
<td>-.00 [-.099, .051]</td>
<td>.00 [-.023, .025]</td>
<td>-.00 [-.026, .022]</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Level 2 (Between group)</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Positive affectivity (GM)</td>
<td>-</td>
<td>.16 [-.098, .419]</td>
<td>.17 [-.055, .432]</td>
</tr>
<tr>
<td>Negative affectivity (GM)</td>
<td>-</td>
<td>.04 [-.218, .304]</td>
<td>.05 [-.22, .311]</td>
</tr>
<tr>
<td>Density</td>
<td>.96 [.183, 1.746]*</td>
<td>.90 [.135, 1.664]*</td>
<td>.88 [.113, 1.655]*</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Cross-level interaction</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>PA (CWG) X PA (GM)</td>
<td>-</td>
<td>-</td>
<td>-.47 [-.357, .350]</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Random Effects</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Slope intercept</td>
<td>-</td>
<td>-</td>
<td>-.01 [-.003, .013]</td>
</tr>
<tr>
<td>Slope residual variance</td>
<td>-</td>
<td>-</td>
<td>.01 [-.009, .029]</td>
</tr>
</tbody>
</table>

| N / parameters               | 267/ 8                     | 267 / 12                                       | 267 / 14                                      |
| Pseudo R² (within)           | .22***                     | .25***                                        | -                                            |
| Pseudo R² (Between)          | .57                        | .62*                                           | -                                            |

***p<.001, **p<.01, *p<.05, CWG = Centred within-group, GM = Grand-mean

Note. Categorical variables in a dichotomous nature, including sex (1 = Female, 2 = Male), authority role (0 = no position of authority, 1 = position of authority) and ethnicity (1 = Caucasian, 2 = Other).
Predicting Status Network Indegree Centrality

Like the interaction network, model-building progressed from initial analyses with descriptive features as predictors in a Random-Intercept Model (Model 1) to then include affectivity variables as predictors of status (Model 2) and finally including a cross-level interaction within a Random Slopes Model (Model 3). Pertaining to Model 3, For the individual-level covariates, age, authority position, and ethnicity were found to be significant in predicting indegree centrality. As such, individuals received more status nominations if they were older ($B = .13, 95\%CI [.029, .23], p < .05$), held an authority position in the club ($B = -.47, 95\%CI [-.053, -.40], p < .001$), and were Caucasian ($B = .09, 95\%CI [.03, .14], p < .01$). Centralization was also found to be significant predictor of the average number of nominations within a group ($B = 1.62, 95\%CI [.98, 2.3], p < .001$), which is in part characterized by the shared mathematical derivation for centralization and indegree centrality (i.e., groups with more nominations are more likely to be relatively more highly centralized). Regarding affectivity, individual positive affectivity did not significantly predict indegree centrality of club members ($B = -.12, 95\%CI [-.63, .39], p = .074$), negative affectivity was a significant predictor ($B = -.12, 95\%CI [.01, .23], p < .05$). Participants with relatively lower negative affect tended to be ascribed with relatively more nominations. As for group-level aggregated affectivity, positive affectivity was found to be significant ($B = 1.12, 95\%CI [.32, 1.8], p < .01$), whereas negative affectivity was not significant ($B = .30, 95\%CI [-.39, .99], p = .39$). Regarding the cross-level interaction, group-aggregated positive affectivity (between-level) did not predict variability in team-level slope between individual positive affectivity (within-level) and indegree centrality ($B = .79, 95\%CI [-1.3, 2.8], p = .45$).
### Table 5

**Multilevel Poisson Regression Models (w/ML) Predicting Indegree Centrality for Status Nomination**

<table>
<thead>
<tr>
<th></th>
<th>Step 1 [random intercept]</th>
<th>Step 2 [random intercept, including affectivity]</th>
<th>Step 3 [random slope, cross-level interaction]</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Level 1 (Within group)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept / Constant</td>
<td>-.17 [.08, 1.2]</td>
<td>.66 [.74, 1.4]</td>
<td>.30 [-.76, 1.3]</td>
</tr>
<tr>
<td>Positive affectivity (CWG)</td>
<td></td>
<td>.09 [-.02, .35]</td>
<td>-.12 [-.63, .39]</td>
</tr>
<tr>
<td>Negative affectivity (CWG)</td>
<td></td>
<td>-.15 [.08, .29]***</td>
<td>-.12 [-.01, .23]*</td>
</tr>
<tr>
<td>Age (CWG)</td>
<td>.09 [-.03, .18]*</td>
<td>.08 [.022, .094]</td>
<td>.13 [.029, .23]*</td>
</tr>
<tr>
<td>Sex (1, 2)</td>
<td>.30 [.12, .48]***</td>
<td>.06 [.07, .31]</td>
<td>.16 [-.06, .38]</td>
</tr>
<tr>
<td>Authority role (0,1)</td>
<td>-.05 [-.54, -.43]***</td>
<td>-.06 [-.53, -.04]***</td>
<td>-.47 [-.53, -.04]***</td>
</tr>
<tr>
<td>Ethnicity (1, 2)</td>
<td>.09 [.04, .14]***</td>
<td>.18 [-.04, .14]***</td>
<td>.09 [.03, .14]***</td>
</tr>
<tr>
<td><strong>Level 2 (Between group)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Positive affectivity (GM)</td>
<td></td>
<td>1.40 [.77, 2.0]***</td>
<td>1.12 [.32, 1.80]***</td>
</tr>
<tr>
<td>Negative affectivity (GM)</td>
<td></td>
<td>.70 [.11, 1.3]*</td>
<td>0.30 [-.39, .99]</td>
</tr>
<tr>
<td>Centralization</td>
<td>2.27 [-.82, 1.15]***</td>
<td>1.63 [1.0, 2.2]***</td>
<td>1.61 [.98, 2.3]***</td>
</tr>
<tr>
<td><strong>Cross-level interaction</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PA (CWG) X PA (GM)</td>
<td></td>
<td></td>
<td>.79 [-1.3, 2.8]</td>
</tr>
<tr>
<td><strong>Random Effects</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Slope intercept</td>
<td>-</td>
<td></td>
<td>.30 [-.76, 1.4]</td>
</tr>
<tr>
<td>Slope residual variance</td>
<td>-</td>
<td></td>
<td>.76 [-.074, 1.6]</td>
</tr>
<tr>
<td>N / parameters</td>
<td>267 / 6</td>
<td>267 / 10</td>
<td>267 / 12</td>
</tr>
<tr>
<td>Loglikelihood</td>
<td>-557.62</td>
<td>-535.27</td>
<td>-516.12</td>
</tr>
</tbody>
</table>

***p<.001, **p<.01, *p<.05, CWG = Centred within-group, GM = Grand-mean

Note. Categorical variables in a dichotomous nature, including sex (1 = Female, 2 = Male), authority role (0 = no position of authority, 1 = position of authority) and ethnicity (1 = Caucasian, 2 = Other). Distinct within- and between $R^2$ values could not be computed across models, because of the Poisson distribution.

Examining the variance at differing levels of the model alongside (pseudo) $R^2$ values from the final models for both interaction and status network (Table 4 and 5) provides further capacity to interpret these findings. First, one observation is that the combination of positive and negative affectivity alongside network indices of group structure explained a substantial amount
of variance in both eigenvector centrality and number of status nominations. For the model in which final individual-level pseudo-$R^2$ values were available, 29% of variance in eigenvector interaction network centrality was predicted. Furthermore, it is evident that based on the small $k$-level sample and heterogeneity across groups, there was relatively little group-level variance. This was evident in relation to the relatively small-to-moderate dependent variable ICCs from .12 to .17, along with the limited between-group residual variance in any model. As such, the most interpretable results from these models pertain to the within-level effects of one’s personality disposition.

**Discussion**

Student clubs, such as those examined in the current research, are contexts in which participants build social connections with their peers. These clubs are an opportunity to establish both friendships with others and garner individual status that can be associated with positive outcomes (Umberson & Montez, 2010). In addition to their significance for individuals, I considered these student clubs as a valuable setting for examining fundamental aspects of group composition and structure that may predict both whom others interact often with, as well as those whom are conferred status. Indeed, the ties among members in small groups can produce networks with complex features, and past research has demonstrated that select personality traits can interact with such features. Using social network analysis within a multilevel framework, I furthered the literature by testing the hypothesis that dispositional positive affectivity coupled with team-level network indices (i.e., density and centralization) will relate to the position (i.e., eigenvector centrality, indegree centrality) an individual occupies within their small group.

The focus of this thesis involved examining how network position was predicted via one’s positive and negative affective disposition in relation to key scenarios. In line with my
individual-level hypothesis focused on how individual affectivity relates to centrality, individual levels of positive affectivity were found to positively predict eigenvector centrality in interaction networks, even after accounting for key covariates at the individual and club level. In contrast, participants’ perceptions of their positive affective reactivity did not significantly predict the extent that individuals gained relatively high or low status nominations from their peers. For status-related models, however, it was individual negative affectivity that was predictive – people with lower negative affect were likely to gain a relatively high number of status nominations. Relative to individual-level findings, tests of group-level hypotheses were generally not significant in either model. I did not find significant associations between the average affectivity across group members and average centrality, nor did I identify significant cross-level interactions. This discussion section will focus on interpreting the contrasting findings relating to status and interaction networks, before considering limitations of this work and potential future directions.

**Interpreting Key Findings**

Recall that Fang and colleagues (2015) in their review found that Big-5 personality traits correlated weakly if at all with that of indegree centrality. In particular, agreeableness, conscientiousness, and extraversion were found to be insignificant. This is despite evidence that individuals high in these traits should find themselves having more positive experiences during social interactions. The current research therefore builds upon Fang and colleagues’ (2015) work by adopting a unique methodology to bridge conflicting findings between the personality and network literature. Relative to common studies from that review, my study leveraged a more ‘narrow’ and inherently social dispositional trait, used specific relational ties (interaction and status), and included more nuanced network constructs to reflect these ties. Accordingly, my
results support the notion that individual personality can play a significant role in how an individual socially orients themselves within small groups. Furthermore, the current research accounted for meaningful group structural differences between different networks through the inclusion of appropriate network constructs (i.e., density and centralization) in my models, and these concepts were often not incorporated within studies reviewed by Fang et al. (2015). One key resulting message is the importance of researchers carefully and purposefully selecting measures and analysis approaches when linking personality with network position.

When considering explanations for the link between positive affectivity and interaction network centrality, several theories reflect on how individuals’ affect comes to shape interactions at work. Several existing theoretical frameworks focus on plausible direct associations, such as how people who often demonstrate positive affect displays are more enjoyable to interact with, sociable, or perceive their networks as broader in nature. However, the Emotions as Social Information Model also suggests that affect has indirect effects on relationships through inferences. van Kleef (2010) specifically articulates how a focal person’s emotions as well as generalized affect shapes the ways in which people interpret and respond to their actions; when someone engages in certain emotional displays, others use that information to make inferences about the focal individual’s intentions and to determine an optimal course of action. For instance, imagine you are in a meeting with your colleagues, and you tell a joke that causes them laugh and be happy. You will make inferences based on their response. For instance, your colleagues’ laughter may lead you to realise that they enjoy your company and that the joke was appropriate (sequence of inferences), motivating you to be funny next time. Their laughter may also make you happy (affective inference), leading you to like your colleagues and cause you to want to
meet more often. This inferential pathway may explain why those people high in positive affectivity were central in interaction networks.

Recall that analyses using peer interaction nominations and eigenvector centrality were replicated with data drawn from status nominations in which participants nominated up to five peers who were admired, respected, and viewed as competent within the group. Unlike that of the interaction network and contrary to my hypothesis, an individual’s tendency to experience positive emotions did not significantly predict one’s ability in garnering indegree status nominations from their peers. Instead, it was the lack of negative affectivity in certain individuals that allowed them to garner the perceived status from their peers even after accounting for individual-level covariates. This finding suggest that friendliness and prosocial aspects normally associated with positive affectivity did not translate to perceived competence and respect from peers. A friendly member of a group may have been rewarded with friendship and interaction from their peers, but this did not predict status. I acknowledge that there is precedent within the status literature for the role of negative affect as a predictor of status within groups. For instance, Anderson et al. (2001) examined status within undergraduate student housing groups and found in male-sex groupings that those with more frequent negative emotion were less likely to gain positions of high status.

One explanation for the significance of negative affectivity as opposed to positive affectivity in how status was conferred is that negative interactions are more salient when determining status, as emphasized by existing literature on negative asymmetry. Specifically, people give disproportionate weight and consideration to negative information and events in decision making and perception in certain contexts. These negative events dominate social judgment due to them contrasting heavily with the positivity that people typically experience
The typical person therefore has a positive bias in expectations during social interactions. As such, negative affectivity and the associated social interaction implications that come with it, stand out and weigh more heavily in how people socially judge others. On the other hand, some researchers argue that during social interactions and other experiences, negative attributes about an individual (e.g., negative affectivity) are less ambiguous than positive information (Birnbaum, 1972; Skowronski & Carlston, 1989). Because of the low ambiguity, people attend to negative attributes as an ‘easier’ path to make social judgements. It is plausible that the conferral of status is particularly influenced by asymmetry, or a negative bias, such that club members who often react negatively to situations are more likely to be attended to – negatively impacting their status conferral. As such, the current research has theoretical implications as it demonstrates that negative asymmetry can extend beyond that of one-on-one social interactions and experiences to that of status perception in small groups.

Though the current research did not set out to empirically compare independent effects between interaction and status network analyses, it nonetheless provided a broader and more descriptive opportunity to contrast interaction and status networks findings. Taking a descriptive approach to networks has been done in the past as shown by Gest and colleagues (2001) in their study examining three distinct dimensions of classroom social position (number of mutual friendships, indegree centrality, status) within elementary students, leveraging correlations to study the relations between the dimensions. Their study serves as an example on how this approach can be beneficial as a preliminary step in making conceptual differences between two networks. Table 5 shows descriptive differences between the two types of networks. For instance, certain individual predictors (i.e., age and authority position) held their significance in both interaction and status networks for predicting embeddedness. Dispositional affectivity, both
positive and negative, played significantly different roles both at an individual and aggregated
group level. I contrast these findings in relation to: (a) conceptual distinctions between affiliative
ties and status nominations, and (b) measurement-related decisions. It should be noted that
negative affectivity was not strongly related to positive affect ($r = .16$). As such, this suggests that
the difference in role and effects is likely not a result of multicollinearity.

**Table 6**

*Contrast Between Individual-level Predictors’ Impact on Interaction and Status Networks*

<table>
<thead>
<tr>
<th>Predictor (Individual Level)</th>
<th>Interaction</th>
<th>Status</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>✔</td>
<td>✔</td>
</tr>
<tr>
<td>Sex</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Position</td>
<td>✔</td>
<td>✔</td>
</tr>
<tr>
<td>Ethnicity</td>
<td>-</td>
<td>✔</td>
</tr>
<tr>
<td>Positive Affect</td>
<td>✔</td>
<td>-</td>
</tr>
<tr>
<td>Negative Affect</td>
<td>-</td>
<td>✔</td>
</tr>
</tbody>
</table>

One important insight is that gaining centrality within interaction networks reflecting
affiliative ties may be contingent on distinct processes relative to status conferral. One theoretical
justification for the contrasting finding lies within the contrasting social processes relating to
status and affiliation. Note that my interaction nomination measure did not overtly request
nominations of friends or those who were well-liked, but nevertheless requested interactions
outside of club meetings – making it affiliative in nature. In contrast, status nominations were
based on competence, respect, and admiration. Some scholars have not drawn clear lines
between these types of nominations. For instance, researchers have operationalized status *using*
patterns in affiliative ties: In one study of adolescents, high status students were identified as
those with many nominations as well as many unreciprocated friendship nominations (i.e., where lower-ranked individual claimed friendship with them, but they did not reciprocate; Ball & Newman, 2013). Other researchers nevertheless draw a distinction between affiliation and status ties, suggesting that although status and interaction networks are similar in social mechanisms and outcome, they differ in the way that they come to form (Brandt & Leskovec, 2014). Importantly, theorists who have worked to establish conceptualizations of status argue for substantial differences in contrast to affiliation. For instance, Djurdjevic and colleagues (2017) in their paper discussing the development of the *Workplace Status Scale*, acknowledge that although popularity and affiliation conceptually overlap with status, status is a distinct construct because individuals may have very high status but low affiliation with others.

My design of the status nomination item relative to the interaction nomination tool may provide a further justification for why positive affectivity was not a significant predictor. The status nomination tool (a) requested reputational responses about status (i.e., how the ‘group’ perceived the target individual) and (b) provided fewer opportunities to nominate others. First, status can be measured at a relational level (i.e., asking a participant to rate their perceptions of each members’ status based on their own beliefs), and at a reputational level (i.e., asking a participant to judge how much the group confers status). If positive affectivity largely functions at a relational level – individuals like and are drawn-to others with high positive affect – then it may have less bearing on overall reputation. Second, narrowing selections to only five individuals may have focused participants particularly toward those with particularly high status and standing within the group, resulting in a range restriction and underpowering of the relationship positive affectivity and status. Other members whom may have moderate status and high positive affect could not be nominated.
Contrasting with individual effects, results suggest that group-level positive affectivity did not significantly relate to how an individual embeds themselves within interaction networks. Furthermore, contrary to my hypotheses, group-level positive affectivity showed no relation to density and centralization for interaction and status networks respectively. As such, my current study does not provide support for my expectations of group-level effects, nor does it support expectations for cross-level interactions. The most important consideration for these findings relates to my small group-level sample. The limited number of clubs examined means that the results for between-group analyses need to be considered cautiously, as a larger sample size could potentially enhance the significance of affectivity group-level predictors and allow for more powerful cross-level interaction analysis. Simulation studies examining the influence of different samples at the group level on the accuracy of estimates in multi-level analysis have found that small samples ($k \leq 50$) at the group level can generate biased estimates of group-based coefficients and standard error (Maas & Hox, 2005). Regardless of my thesis’ sample size, the inclusion of these Level 2 predictors was necessary to account for unique variances that structural differences between clubs may account for in my Level 1 analysis.

Theoretical implications aside, my research also has practical implications in regard to how new employees should behave in team settings in order to situate themselves in favourable positions. Recall that my current study found contrasting associations between positive reactivity and interaction and status relational ties, this suggests that employees might consider what type of relational tie they are attempting to foster with other members. For instance, applying this example to a workplace context, one instance might be during the socialization process: Positive affectivity may enable new members to an organization to become embedded and well-known, but might not function to aid an individual in climbing the 'ladder' that is the status hierarchy.
One interesting – albeit indirect – practical implication relates to whether people high in positive affectivity who become embedded within the group influence affect of those around them. There is evidence to suggest that interpersonal ties between individuals can be a pathway for social influence. For instance, the concept of *emotional contagion* is defined as processes that allow the sharing or transfer of emotions from one individual to other group members, often occurring without conscious knowledge (Barsade, 2002). This everyday, continuous, and automatic process has been described as a tendency to mimic the nonverbal behavior of others, to “synchronize facial expressions, vocalizations, postures, and movements” with others, resulting in a convergence of emotions (Hatfield, Cacioppo, & Rapson, 1994). Past research on the relationship between affect and work-related performance have demonstrated that certain fields, such as that of sales, directly benefit from ‘positive employees’ as they generate more sales when interacting with customers (Sharma & Levy, 2003). Although I did not directly test social influence expressed through interaction networks, organisations may benefit from identifying employees with high positive affectivity beyond that of increased performance, as these individuals are likely to position themselves into central and important positions in social groups, and therefore be in the optimal position to ‘spread’ their positive affect to other employees.

**Future Research/Limitations**

The current study has numerous strengths. I collected in-person data that included students embedded within small groups with significance in their lives and with clear interdependent group tasks, so it is applied research with meaning for participants. I also adopted a network-based nomination approach to provide an in-depth examination of how affectivity can impact position in a social group. This network approach was beneficial to (a) avoid issues that arise with single-source data collection, and (b) examine constructs that are
derived based upon group structure rather than the mere number of nominations (i.e., eigenvector centrality; centralization). This study nevertheless has several limitations beyond the small group-level sample size described above. The first limitation involves variability in size and type of club context. I adapted the network constructs in ways that reduce issues relating to some between-groups differences, but several additional sources of heterogeneity relate to variability in frequency of meetings, club norms for interaction, and markers of social identity that may unite members (i.e., racial or ethnic background; major in university; shared interests, year of study, cultural background). Although there are benefits to sampling a wide variety of clubs, heterogeneity across networks presents unique challenges. This heterogeneity may indeed shape how individuals come to interact with others and impact the network in terms of how groups come to structure themselves (i.e., density, centralization). For instance, past research examining how affiliative or competitive group context can impact the relationship between personality and status attainment found that extraversion predicted status in both contexts, whereas agreeableness was only associated with status in affiliative context (DesJardins et al., 2015). Such research demonstrates the importance of considering context when examining social relations like status attainment. Future research should attempt to examine ‘similar’ types of groups to reduce heterogeneity, or design adequate measures of social context to better integrate types of groups in their analysis to examine between-group heterogeneity.

My models accounted for a significant amount of variance in the dependent variables, but one limitation relates to how that variance is distinguished and accounted for. I adopted a network perspective to examine individual and group levels of interaction in small clubs, and extracted network variables to be used within a multilevel analysis framework. Multilevel analyses account for interdependence in data shared across members of a group, but this is not
able to distinguish the unique variance shared within certain dyads. Multilevel approaches cannot account for variance shared by members linked via nomination, nor can they examine predictors or outcomes at the dyadic or network level. As such, there remains the question of whether dyadic relationships between members or network-level structures could account for this remaining variance.

Regarding shared variance based on network proximity, a potential extension for the current study involves the use of exponential random graph modeling (ERGM) to identify additional processes that may influence the creation of edges/links between different nodes and how this can shape the global structure of a network (Hunter et al., 2008). The focus of ERGM is on the factors predicting any given tie between members. Whereas such analyses were beyond the scope of this project, one could model dyadic and higher-order dependencies and therefore ask more complex and nuanced questions. For instance, within the context of the current study, perhaps parallel interaction nominations, wherein two individuals nominate each other as friends, are more likely to occur if two individuals are of the same gender or ethnicity. Alternatively, for parallel status nominations, maybe similarity between individual’s age and position within clubs is the main driver.

A second extension for the current study is the application of an experimental design to test the causality of positive affectivity on social relations position in small groups. As previously discussed, despite evidence that positive affect ‘matters’, the specific findings about positive affectivity vary across studies. The existing literature in groups often involve small and observational designs where many confounding variables can impact effects. As such, it is apparent that experimental research within the personality and group literature is needed. Researchers may therefore consider novel in-lab paradigms to manipulate positive affectivity in
small work teams to examine the underlying social mechanisms on how individuals with high positive affective reactivity develop relational ties with others. For instance, researchers could manipulate participants’ affective behaviour and examine the number of quantity and qualities of interactions they have with other members. From a dyadic perspective, researchers can test for emotional contagion and directly manipulate other member’s affective behaviour and examine how this directly influences the affective behaviour of other members and the quantity or quality of interactions between them.

Lastly, my decision to utilise peer-nomination to create networks does not allow for full control of missing members within clubs. One could argue that this missingness is representative of student club life as there is large variability in the membership boundaries of such groups in general. Nonetheless, complete networks allow for more complex questions to be asked, and more concrete conclusions to be drawn. Although my analyses suggests that there were comparatively few highly nominated members who did not complete surveys, future research should attempt to replicate my design with a roster-nomination method that involves garnering a complete roster of group members from leaders and providing that roster to individuals as a means to prompt responses. This helps to establish what the complete roster of members is and would ensure that missing nominations were not simply because participants did not recall another member. Much of the challenge with engaging in a roster-based approach is ethical: Whereas I initially proposed a roster-based approach with the ethical review board, this was deemed a risk to participant anonymity and consent to be involved in research. Perhaps future network research should work alongside ethical review teams to design studies that mitigate participant risk while also developing scientific rigour.

Conclusion
In this study, I examined the role that dispositional positive affectivity plays in how one socially positions themselves in university student clubs. I found that positive reactivity predicted embeddedness (i.e., eigenvector centrality) for interaction networks whereby higher reactivity led to members being central and connected to other ‘embedded’ members. Negative reactivity was found to predict conferred status nominations from other peers (i.e., indegree centrality) for status networks whereby lower negative reactivity led to more status nominations from peers. Club-aggregated positive reactivity failed to predict network structural constructs for both interaction and status networks, whilst also failing to interact with individual positive reactivity in cross-level analysis. This work builds upon past research examining the relationship between personality traits and network position in groups by utilising more nuanced network constructs coupled with a narrower personality trait. Furthermore, my study makes the distinction between interaction and status networks. Moving forward, researchers are encouraged to replicate the study in distinct contexts, while also considering different methodologies that either further incorporate network processes that explain the prominence of members (i.e., using ERGM) or establish the causal effect and mechanisms for the influence of member affect on correlates.


https://doi.org/10.1016/j.socnet.2011.10.003


https://doi.org/10.1007/978-94-007-6772-0_3


https://doi.org/10.1177/1088868314544467


https://doi.org/10.1287/orsc.1100.0643


Xu, T., Evans, M. B., & Benson, A. (Under review). The nature of status: Navigating the diverse approaches to conceptualizing and measuring status.
Appendix A

Peer Interaction Nomination

**INSTRUCTIONS:** In the spaces below, please list the names (max 10) of club members whom you have spent time with, outside of club activities, at least once in the past several months.

<table>
<thead>
<tr>
<th>Club Member #1</th>
<th>_________________________</th>
</tr>
</thead>
<tbody>
<tr>
<td>Club Member #2</td>
<td>_________________________</td>
</tr>
<tr>
<td>Club Member #3</td>
<td>_________________________</td>
</tr>
<tr>
<td>Club Member #4</td>
<td>_________________________</td>
</tr>
<tr>
<td>Club Member #5</td>
<td>_________________________</td>
</tr>
<tr>
<td>Club Member #6</td>
<td>_________________________</td>
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<tr>
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<td>_________________________</td>
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<tr>
<td>Club Member #8</td>
<td>_________________________</td>
</tr>
<tr>
<td>Club Member #9</td>
<td>_________________________</td>
</tr>
<tr>
<td>Club Member #10</td>
<td>_________________________</td>
</tr>
</tbody>
</table>
Appendix B

Peer Status Nomination

INSTRUCTIONS: In the spaces below, please list the names (max 5) of club members that you believe are respected, admired, and show competence when it comes to club activities.

[Use the first and last name for each person, e.g., 'Taylor White']

Club Member #1 _______________________

Club Member #2 _______________________

Club Member #3 _______________________

Club Member #4 _______________________

Club Member #5 _______________________

Appendix C

Emotional Reactivity, Intensity, and Preservation Scale (Ripper et al., 2018)

INSTRUCTIONS: This scale consists of a number of words that describe different feelings and emotions. When exposed to a situation that would make the “average” person experience this feeling, how likely is it that you will experience this particular feeling? Please rate this using the five options provided.

<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></td>
<td>Highly unlikely</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
</tbody>
</table>

1. Interested
2. Excited
3. Strong
4. Enthusiastic
5. Proud
6. Alert
7. Inspired
8. Determined
9. Attentive
10. Active
11. Distressed
12. Upset
13. Guilty
14. Scared
15. Hostile
16. Irritable
17. Ashamed
18. Nervous
19. Jittery
20. Afraid
Appendix D

Demographics Question

INSTRUCTIONS: The following demographic questions will help us to describe the characteristics of our study sample. Any information you provide is strictly confidential and you can decline from responding to any question by leaving it blank. For questions you find difficult to answer, just provide your best guess

1. What is your age? _____ years old

2. What year of study are you currently in? _______

3. What is your gender?
   - Male
   - Female
   - Prefer not to say
   - I identify as…. __________

4. Please indicate the position that best describes you within your student club.
   - President
   - Vice President
   - Secretary
   - Treasurer
   - Member
   - Other _______

5. Please indicate the broad ethnic group that best describes you:
   - African/Black
   - Aboriginal
   - East Asian
   - European/Canadian/White
   - Latino/Hispanic
   - Middle Eastern
   - South Asian
   - Other _______
Appendix E

Reactivity Justification

My decision to only utilise the reactivity sub-scale of the ERIPS was due to participants being confused regarding the different sub-scales and how they were different from each other. As a result, participants often left the intensity and preservation parts of the ERIPS blank. This is reflected in my preliminary analysis of missingness. Little’s (1998) test of missing completely at random (MCAR) revealed that the ERIPS used to measure trait affectivity was significant, \( \chi^2 (1433, N = 317) = 1647.63, p < .05 \), suggesting that the participants were systematically not responding to certain items. Follow-up analyses aligned with initial observations of participants, indicating patterns of missingness were largely pertaining to items from the intensity and preservation subscales. This prompted me to utilise only the reactivity component of the scale. A subsequent Little’s (1998) MCAR test of just the reactivity subscale justified this decision as the test came back insignificant, \( \chi^2 (94, N = 317) = 94.6, p < .05 \), suggesting that no item was systematically missing in data. To counter this issue, I decided to discard the latter intensity and preservation component of the ERIPS and solely use the reactivity subscale – which also demonstrated high internal consistency.
Appendix F

Mplus Code for Multilevel Analysis

Interaction

DATA:
FILE = C:\Users\Evans Lab\Desktop\SPSS_MPLUS_REPA_MANA31_EVERYTHING.dat

VARIABLE:
NAMES = KEVIK Eig_F In_F Clust Out R_Av I_Av Rep_Eig ST
In_S Out_S Tot_Deg_S Ess_S Clust_S Clust_Tp Node_Gr Edge_Gr NoResGr AvDegGr
ClustGR MdlDr ClubDen Gr NodGr Eds NodGr S AvDegs NodGr S Dens_S
Cluster_Gr S CentrAlg CentrB CentrD CentrS TSAMرغ RAVM RAVM
RVAVm AveGR GRAGM RAVAGM RAVAGM GrpGrp EssGrp Clust_Gr OutGr RepRep RepE
Ethn Age YOY Autho Post Gender Di_Eth GPA v67-v113 ID
USEVARIABLES = Club Eig_F RepA Age RepA
Gender Autho Di_Eth RAPAGM RandGM Dens_Gr;
CLUSTER = Club;
MISSING ARE ALL(-999);
WITHIN = Age RepA RepA Gender Autho Di_Eth;
BETWEEN = RAPAGM RandGM Dens_Gr;
DEFINE:
CENTER Age RepA RepA (groupMEAN);
CENTER RAPAGM RandGM (GRANDMEAN);

ANALYSIS:
TYPE = TWOLEVEL random;
ESTIMATOR = ml;

MODEL:
%WITHIN%
 s | Eig_F ON RepA;
Eig_F ON AGE RepA Gender Autho Di_Eth;
%BETWEEN%
Eig_F ON RAPAGM RandGM Dens_Gr;
[s] (gam0);
s ON RAPAGM (gam1);
Eig_F WITH s80;

OUTPUT:
cinterval standardized

Status

DATA:
FILE = C:\Users\Evans Lab\Desktop\SPSS_MPLUS_REPA_MANA31_EVERYTHING.dat

VARIABLE:
NAMES = KEVIK Eig_F In_F Clust Out R_Av I_Av Rep_Eig ST
In_S Out_S Tot_Deg_S Ess_S Clust_S Clust_Tp Node_Gr Edge_Gr NoResGr AvDegGr
ClustGR MdlDr ClubDen Gr NodGr Eds NodGr S AvDegs NodGr S Dens_S
Cluster_Gr S CentrAlg CentrB CentrD CentrS TSAMرغ RAVM RAVM
RVAVm AveGR GRAGM RAVAGM RAVAGM GrpGrp EssGrp Clust_Gr OutGr RepRep RepE
Ethn Age YOY Autho Post Gender Di_Eth GPA v67-v113 ID
USEVARIABLES = Club In_S RepA RepA Gender Autho Di_Eth GPA;
CLUSTER = Club;
MISSING ARE ALL(-999);
COUNT = In_S (n);
WITHIN = Age RepA RepA Gender Autho Di_Eth;
BETWEEN = RAPAGM RandGM CentrAl;
DEFINE:
CENTER Age RepA RepA (groupMEAN);
CENTER RAPAGM RandGM CentrAl (GRANDMEAN);

ANALYSIS:
TYPE = TWOLEVEL random;
ESTIMATOR = ml;

MODEL:
%WITHIN%
 s | In_S ON RepA;
In_S ON AGE RepA Gender Autho Di_Eth;
%BETWEEN%
In_S ON RAPAGM RandGM CentrAl;
[s] (gam0);
s ON RAPAGM (gam1);
In_S WITH s80;

OUTPUT:
cinterval standardized
Appendix G

Ethics Approval

Date: 10 August 2022

To: Dr. Michael Evans

Project ID: 120870

Study Title: Predicting Influence and Position in University Student Groups: A Social Network Approach

Short Title: Small Group Social Network Survey

Application Type: NMREB Initial Application

Review Type: Delegated

Full Board Reporting Date: 09/Sept/2022

Date Approval Issued: 10/Aug/2022 10:32

REB Approval Expiry Date: 10/Aug/2023

Dear Dr. Michael Evans,

The Western University Non-Medical Research Ethics Board (NMREB) has reviewed and approved the WREM application form for the above mentioned study, as of the date noted above. NMREB approval for this study remains valid until the expiry date noted above, conditional to timely submission and acceptance of NMREB Continuing Ethics Review.

This research study is to be conducted by the investigator noted above. All other required institutional approvals and mandated training must also be obtained prior to the conduct of the study.

Documents Approved:

<table>
<thead>
<tr>
<th>Document Name</th>
<th>Document Type</th>
<th>Document Date</th>
<th>Document Version</th>
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<td>CLEAN 4.1.9T Forwarded Email To Missing Members (120870) V2</td>
<td>Recruitment Materials</td>
<td>23/Jun/2022</td>
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<td>Online Survey</td>
<td>15/Jul/2022</td>
<td>3</td>
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No deviations from, or changes to the protocol should be initiated without prior written approval from the NMREB, except when necessary to eliminate immediate hazards to study participants or when the changes involve only administrative or logistical aspects of the trial.

The Western University NMREB operates in compliance with the Tri-Council Policy Statement Ethical Conduct for Research Involving Humans (TCP2S), 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 REB. The NMREB is registered with the U.S. Department of Health & Human Services under the IRB registration number IRB 00000041.

Please do not hesitate to contact us if you have any questions.

Sincerely,

Ms. Zoë Levi, Research Ethics Officer on behalf of Dr. Randal Graham, NMREB Chair

*Note: This correspondence includes an electronic signature (validation and approval via an online system that is compliant with all regulations).*
Appendix H

Curriculum Vitae for Roy Hui

ROY HUI

Education

**M.Sc.** Industrial/Organizational Psychology; Biology Minor *(in progress)* 2021 - 2023

*Western University, ON, Canada*

**Master’s Thesis Title:** Affectivity and its Role in Predicting Sociometric Position in Small Group Networks

**BSc** Honours Psychology; Biology Minor 2016 - 2021

*University of Waterloo, ON, Canada*

**Honours Thesis Title:** Viewing things from your boss's side: Investigating how perspective taking can restore one's sense of justice following abusive supervision

Honors and Awards

- SSHRC: Canadian Graduate Scholarship - Master’s Scholarship (2022)
- Ontario Graduate Scholarship (2021)
- Douglas N. Jackson Memorial Award (2021)
- Undergraduate Thesis Award (2020)
- 2nd Place Canadian Society for Industrial/Organizational Psychology Student Poster Award (2019)
- Term Dean’s Honour Roll (Achieved for 5 terms)
- UW President’s Scholarship (2016)

Publications

**Extended Abstract and Roundtable**


**Published Abstract and Poster Presentation**


Research Experience

**Master’s Thesis (In progress)** 2021-2023
Department of Psychology, Western University

**Honours Thesis**

2019-2020

Department of Psychology, University of Waterloo

**Defence Research Assistant**

2019-2019

Department of National Defence (DND) – DRDC Toronto, Canada

**Liang’s Lab, Research Assistant**

2018-2019

Department of Organizational Behavior and HRM, Wilfrid Laurier University

**Brown’s Lab, Research Assistant/Lab Manager**

2017-2018

Department of Psychology, University of Waterloo

**Teaching Experience**

<table>
<thead>
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- Psychology 3694 - Teams and Work Groups in Organizations
- Psychology 2820E - Research Methods and Statistical Analysis in Psychology