3-28-2022 12:30 PM

Learning Analytics for the Formative Assessment of New Media Skills

Negar Shabihi, *The University of Western Ontario*

Supervisor: Dr. Mi Song Kim, *The University of Western Ontario*
A thesis submitted in partial fulfillment of the requirements for the Master of Arts degree in Education

Abstract

Recent theories of education have shifted learning environments towards student-centred education. Also, the advancement of technology and the need for skilled individuals in different areas have led to the introduction of new media skills. Along with new pedagogies and content, these changes require new forms of assessment. However, assessment as the core of learning has not been modified as much as other educational aspects. Furthermore, Although automatic evaluation methods can offer numerous opportunities to develop new assessment scenarios, in some cases, they are only computer-based forms of traditional methods. Hence, much attention is required to develop assessment methods based on current educational requirements. To address this gap, we have implemented two data-driven systematic literature reviews to recognize the existing state of the field in the current literature. Chapter four of this thesis focus on a literature review of automatic assessment, named learning analytics. This chapter investigates the topics and challenges in developing new learning analytics tools. Chapter five studies all assessment types, including traditional and automatic forms, in computational thinking education. Computational thinking education, which refers to the teaching of problem-solving skills, is one of the new media skills introduced in the 21st century. The findings from these two literature reviews categorize the assessment methods and identify the key topics in the literature of learning analytics and computational thinking assessment. Studying the identified topics, their relations, and related studies, we pinpoint the challenges, requirements, and opportunities of using automatic assessment in education. The findings from these studies can be used as a guideline for future studies aiming to enhance assessment methods in education. Also, the literature review strategy in this thesis can be utilized by other researchers to develop systematic data-driven literature reviews in future studies.

Keywords

Learning Analytics, Multimodality, Big Data, Computational Thinking, New media, Assessment

Summary for Lay Audience

Evaluation of students' learning is a key factor in education. Assessment of learning has various benefits in different educational levels. At the organizational level, assessing students' learning provides an overview of the effectiveness of educational methods, tools, content, and equipment. Teachers utilize assessment to support students' learning or evaluate their own teaching strategies at the school or class level. Also, assessment of learning allows students to learn by critically reviewing and reflecting on their own or their peers' learning. Acknowledging the importance of assessment, some researchers call assessment the core of learning. However, assessment has not been well studied in the literature, and the findings from empirical studies indicate that more studies are required to achieve assessment methods suitable for the new pedagogical and curriculum requirements. This thesis studies the current literature of assessment in education. Targeting the new assessment methods suitable for the latest and changing education requirements, we focus on automatic assessment forms. Automated assessment scenarios use computer-based algorithms and methods to assess educational data. In a separate section, we also study different assessment methods in a recent educational field, computational thinking, to investigate the new requirement for assessing 21^{st}-century skills. Based on the results, the thesis provides suggestions and possible future directions.

Co-Authorship Statement

This integrated-article thesis consists of two research papers co-authored with Dr. Mi Song Kim. Chapter four of this thesis has been published in the proceeding of the International Conference of Advanced Learning Technologies (ICALT 2021), and chapter five has been published in the proceedings of the European Conference in eLearning (ECEL 2021). Dr. Mi Song Kim, as my supervisor, provided guidance and feedback for the studies, and she fully supports the inclusion of the articles as chapters for Negar Shabihi's master dissertation.

Acknowledgments

I would like to thank my supervisor Dr. Mi Song Kim for guiding me throughout my work, including me in her research projects, and giving me the freedom to explore, learn, and follow my curiosity. I would also like to thank my research committee member Professor Charles Ling for sharing his ideas and helping me to enrich my work.

I thank Professor Dan Remenyi, the chair of the European Conference on e-Learning (ECEL 2021), who provided constructive and helpful comments on my presentation and paper, during and after the conference. Also, a big thank you to all my influential professors at Western, especially Dr. Isha Decoito, who encouraged me in the first steps and gave me the confidence to work on an interdisciplinary thesis.

Also, I want to thank my colleagues and friends at Western, I truly appreciate your support and friendship. In particular, I would like to thank Najmeh Keyhani, a Ph.D. graduate from our research team, who was always available to answer my questions or review my paper during stressful times.

And finally, I would like to thank my parents and my spouse, Mohammad, who has been endlessly encouraging and patient.

This thesis was supported by the AER Graduate Scholarships for Literacy Studies in Education. This scholarship was established with Foundation Western by a generous gift from an anonymous donor.

Table of Contents

Abstract ii

Summary for Lay Audience iv

Co-Authorship Statement v

Acknowledgments vi

Table of Contents vii

List of Tables xi

List of Figures xii

Chapter 1 1

1 Introduction 1

1.1 Problem Statement 2

1.2 Purpose Statement 4

1.3 Research Questions 6

1.4 Overview of Remaining Chapters 7

Chapter 2 8

2 Literature Review 8

2.1 Multiliteracies Assessment in Technology-Enhanced Learning 8

2.1.1 New media skills 8

2.1.2 Multiliteracies 9

2.1.3 Multiliteracies Assessment 10

2.1.4 Multiliteracies Pedagogical Framework 10

2.2 Computational Thinking and Assessment 11

2.2.1 Computational thinking 11

2.2.2 Computational Thinking Assessment 13

2.3 Learning Analytics for Learning Assessment 14

2.3.1 Learning Analytics: Theory and Definition 15

2.3.2 Learning Analytics: Dimensions 16

2.3.3 Learning Analytics and Big Data 19

2.3.4 Multimodal Learning Analytics 20

2.3.5 Visualization and Reporting Learning Analytics 23

Chapter 3 25

3 Methodology 25

3.1 Systematic Data-Driven Literature Review 25

3.1.1 Stage 1: Formulating a Research Question 26

3.1.2 Stage 2: Information Source 27

3.1.3 Stage 3: Search Strategy 27

3.1.4 Stage 4: Selection Strategy 27

3.1.5 Stage 5 and 6: Data Analysis Method and Process 28

3.1.6 Stage 7: Synthesis 32

Chapter 4 33

4 Data Analytics in Education: A Data-Driven Literature Review 33

4.1 Introduction 33

4.2 Challenges and issues of big data analytics in educational research 35

4.3 Method 36

4.3.1 Data Collection 36

4.3.2 Data Selection 37

4.3.3 Data preprocessing 37

4.3.4 Data Analysis 38

4.4 Results 39

4.4.1 Big Data in Learning Analytics: Topics 39

4.4.2 Network Analysis of Identified Topics 43

4.5 Discussion 44

4.6 Conclusion 46

4.7 References 47

Chapter 5 51

5 Data-Driven Understanding of Computational Thinking Assessment: A Systematic Literature Review 51

5.1 Introduction 52

5.2 Literature Review 53

5.2.1 Computational Thinking 53

5.2.2 Computational thinking assessment 54

5.3 Method 54

5.3.1 Data collection 55

5.3.2 Data Selection 55

5.3.3 Data preprocessing 56

5.3.4 Data analysis 56

5.4 Findings 56

5.4.1 Computational Thinking Assessment Topics 57

5.4.2 Network and Factor Analysis 61

5.5 Discussion 61

5.5.1 Diagnostic Assessment 63

5.5.2 Formative Assessment 63

5.5.3 Summative Assessment 64

5.5.4 Self-assessment 65

5.5.5 Peer Assessment 65

5.5.6 Assessment to Transfer Skills 65

5.5.7 Learning Analytics for Assessment 66

5.5.8 Mixed-Method Assessment ... 67

5.6 Conclusion ... 67

5.7 References ... 69

Chapter 6 ... 74

6 Conclusion ... 74

6.1 Review of the Research Questions ... 74

6.2 Summarizing the chapters ... 74

6.2.1 Chapter four: A literature review of Learning Analytics ... 74

6.2.2 Chapter five: Computational Thinking Literature Review ... 76

6.3 Research contribution ... 77

6.4 Future work ... 78

References ... 81

Curriculum Vitae ... 91

List of Tables

Table 1: Overview of Data Collection 37

Table 2. Overview of Data Collection and Data Selection 55

List of Figures

Figure 1: The two articles in the thesis and their interconnection 6

Figure 2 The stages of the systematic literature review in the two studies of the thesis 26

Figure 3: The process of finding a Core Vector Space 30

Figure 4: A sample results from the four metrics used for identifying an optimal number of topics for LDA 32

Figure 5. Six research topics of big data analytics in education 39

Figure 6. A network of research topics in educational big data analytics 45

Figure 7. A three-dimensional model of categories in big data and learning analytics research 45

Figure 8. Identified Research Topics for CTA 58

Figure 9. Network of research topics 61

Chapter 1

1 Introduction

The advancement of technology and the widespread use of the internet have changed learning and teaching structures and shifted the educational environments toward technology-enhanced settings. These changes facilitated social interactions and ease of access to learning material. Moving toward technology-enhanced learning (TEL) and teaching provides the opportunities to respond to the developments in education and teaching science, such as student-centred learning. However, there has been a much slower shift in changing methods to provide assessment and feedback (Sweeney et al., 2017).

Except for the existing non-technological challenges of assessing students' learning, technology has introduced additional assessment processes. TEL can support a higher number of students along with various and complex forms of data. Also, in TEL, students' activities can be collected from different sources. These characteristics of learning in TEL add additional complexities to the assessment in education. Furthermore, the necessity of evaluating new skills, named new media skills, introduces another challenge. New media skills are the required skills for students to perform as influential members of society (Jenkins, 2006) and include skills such as problem-solving that are difficult to assess. Also, while these skills are supposed to be taught in primary and middle schools, most existing studies are related to higher education. This thesis uses a novel quantitative approach for analyzing the relevant literatures in education to address the challenges regarding the assessment of learning in education. Our quantitative literature review method analysis previous articles in the field using topic modeling and social network analysis methods. Along with the analysis result, including different themes and topic in the literature and their connection, the thesis provides a three-dimensional model of automatic assessment in education to address the different areas that impact the assessment of learning. The following section explores assessment challenges and the possibilities of using automatic assessment methods to improve the assessment of learning.

1.1 Problem Statement

Assessment is the core of learning; however, it is cited as the most dissatisfaction source for students (Ferrell, 2012). Theories of learning and teaching emphasize the claim that cognitive abilities are developed through social interactions, active construction of knowledge, and sense-making (Vygotsky, 1978). These theories support the need for evaluating higher-order skills, self-regulated learning, and peer assessment (Oldfield, Broadfoot, Sutherland, & Timmis, 2012). Also, the tendency to shift from summative to formative forms of assessment, which refers to the change from assessment of learning to the assessment for/as learning, requires new assessment methods (Sweeney et al., 2017). Students' engagement and empowerment in the assessment process are essential to fulfill these goals. The use of automatic methods for formative assessment can provide timely and insightful feedback for both educators and students.

Except for the challenges of applying educational theories to the assessment process, technology introduces new constraints to the human-based assessment methods. TEL environments can support a higher number of students in a learning course. Also, students' activities and artifacts in these courses can be monitored and stored from different sources and various data formats. While human-based assessment methods may not be efficient for assessing data from a higher number of students and multiple sources, automatic assessment methods can support various data formats and a higher volume of data.

Also, the advancement of technology has coined the necessity of learning new skills necessary for students to perform better in real-life settings. Jenkins (2006) believes that nowadays, along with the traditional skills, students have to learn additional skills to perform better as members of our technology-dependent society. These new skills are named new media or multiliteracies skills (Dawson & Siemens, 2014; Jenkins, 2006) and are categorized into 11 groups of skills, including play, performance, simulation, appropriation, multitasking, distributed cognition, collective intelligence, judgment, transmedia navigation, networking, and negotiation Jenkins (2006). Scholars believe that the assessment of these skills is challenging and requires new assessment methods. Schilder, Lockee, & Saxon (2016) state that the major challenge in assessing students' new media skills is the lack of systematic implementation of new media skills and their corresponding assessment tools. That is while automatic assessment methods can assist educators and researchers to understand the hidden aspects in the data collected from students' activities and analyze students' new media skills.

Finally, there is an age gap in the literature of TEL regarding the assessment methods. In recent years, utilizing TEL in school grades has paved the way for more innovative and student-centred educational environments. However, most assessment methods are related to higher education (Pishtari et al., 2020). While multiliteracies skills are mainly aimed to be taught at pre-university levels, there is not much implementation of suitable methods to enhance learning assessment for schoolers. Also, the literature indicates a gap regarding systematic research on the challenges and possibilities of utilizing automatic assessment methods in school grades, especially for the assessment of new media skills.

1.2 Purpose Statement

Intending to facilitate the assessment in education, in recent years, different scholars have studied data science methods for the automatic evaluation of students' learning and skill acquisition in the process of learning (Aung, 2017; Blikstein & Worsley, 2016; Gutierrez et al., 2018). Data science refers to developing tools and processes to extract valuable knowledge from complex data (Daniel, 2019). Data science in education is primarily concerned with using automatic data analysis techniques to evaluate the data collected from learning environments. Based on the abovementioned challenges in learning assessment, in this thesis, I aim to explore existing data science techniques that can enhance assessment in education.

Data science techniques can be utilized to analyze different levels in educational settings, including individual, class, school, or organizational levels (Adeniji, 2019). For instance, while some studies use data science techniques to monitor, analyze, and predict students' learning, such as the early prediction of academic success to allow teacher interventions (Avella, Kanai, & Kebritchi, 2016), other studies are concerned about enhancing educational institutions' performance and decision making (Quadir, Chen, & Isaias, 2020). This thesis will mainly focus on Learning Analytics (LA), which refers to implementing data science methods to analyze students' individual and class level activities in the process of learning (Avella et al., 2016). Also, a specific field of education, named computational thinking, is selected to study the impact of utilizing data science techniques for assessment purposes. In the form of an integrated article thesis, this thesis includes two articles explained in the following.

The first article explores the LA literature and presents a systematic review of the LA research items. This article studies the LA literature's methods, applications, theories, and trends. Also, the article synthesizes the challenges of using LA in education. Based on the LA literature, data analysis in educational environments can assist human-based evaluations and make the assessment practices time-efficient and flexible (Brinkhuis et al., 2018). However, without considering educational theories, LA cannot solely solve the challenges of evaluating students' educational skills, especially for the multiliteracies skills.

The second article of the thesis focuses on the use of LA to enhance the assessment of new media skills for schoolers. Multiliteracies skills include a broad range of skills and can be taught through different courses. Teaching Computational thinking (CT) to schoolers is one of these areas. CT is introduced as Computational Literacy (Jacob & Warschauer, 2018) and intends to enhance students' problem-solving skills based on concepts fundamental to computer science (Wing, 2006). Different scholars have studied various assessment methods to evaluate students' CT skills in recent years. These methods include both human-based and automatic assessment methods. However, most of the automatic assessment methods for CT assessment are limited to the analysis of computer-based and programming skills rather than problem-solving and multiliteracies skills. Also, there is no systematic mapping of CT skills, related new media skills, and suitable automatic assessment methods for CT assessment. Reviewing the literature of CT assessment and exploring possible LA methods to analyze these skills is the focus of the second article in the thesis.

Figure 1, shows the two articles of the thesis and their interconnections.

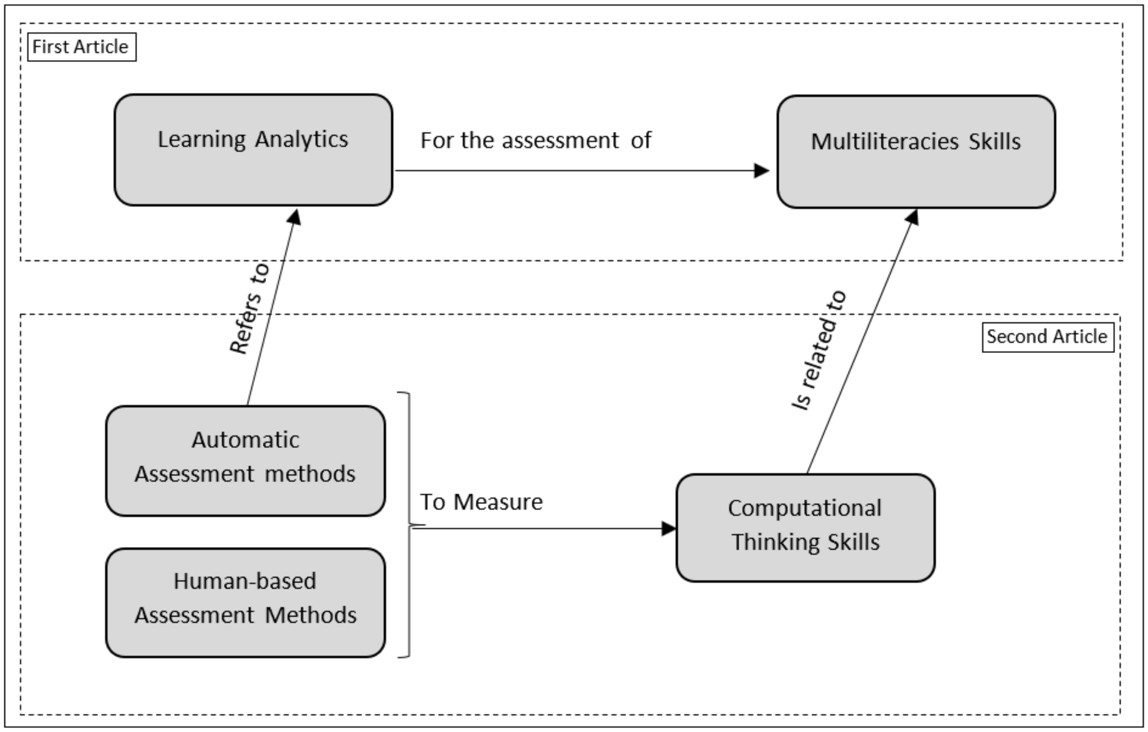

Figure 1: The two articles in the thesis and their interconnection

1.3 Research Questions

The research questions for each of the two articles mentioned above are as follows. For the first article, the research questions include 1) RQ1.1: What are the methods and applications of automatic data analysis in education? 2) RQ1.2: What are the trends and general topics in the literature of LA? 3) RQ1.3: How can LA methods be used to assess multiliteracies skills? For the second article, the research questions include 1) RQ2.1: What are the trends and general topics in the literature of CT assessment? 2) RQ2.2: what are the CT skills and their existing assessment tools in the literature of CT assessment? 3) RQ2.3: How can LA methods be utilized to enhance the assessment of CT skills?

The two studies in chapters four and five answer the above questions. The remaining questions are discussed and interpreted in the discussion chapter based on the results from both studies. Finally, the discussion chapter has listed all the research questions and their corresponding answers.

1.4 Overview of Remaining Chapters

This integrated article thesis consists of six chapters. Chapter two provides a literature review of the related fields and key thesis concepts, including learning analytics, computational thinking assessment, and assessment of new media skills. Chapter three presents the designed methodology for the thesis's two articles. Both research articles of this thesis are conducted as systematic literature reviews.

Chapter four explores the literature on learning analytics and focuses on big data analytics in education to ensure the retrieved research items are related to multimodal assessment of students' learning. Learning analytics trends and methods are discussed in this chapter. Also, the chapter addresses the research questions related to learning analytics.

In chapter five, the literature of computational thinking assessment was studied. This chapter presents 11 topics in CTA literature and explores their interconnections. Also, the chapter answers the research questions related to CTA. The automatic form of assessment and challenges of implementing CTA is also discussed in this chapter.

The sixth and final chapter in this thesis is the concluding chapter. This chapter summarizes the two thesis articles and corresponding findings to the research questions. Also, chapter six includes the thesis's contribution and possible future research directions.

Chapter 2

2 Literature Review

2.1 Multiliteracies Assessment in Technology-Enhanced Learning

Technology-Enhanced Learning (TEL) is concerned with the use of technology to support learning, whether the learning is local or remote. Technology in education refers to the use of computer-based technologies in the process of learning (Westera, 2010). Learning can be considered as a process, and learning through technology seeks to improve that process. Some scholars have used other terms instead of TEL, including ‘e-learning,’ ‘learning technology,’ and ‘computer-based learning’ (Bayne, 2015). TEL offers flexibility, scalability, and new methods to facilitate learning and teaching. Learning in TEL environments requires students to learn new forms of skills, which students need in real-life settings surrounded by technological devices.

2.1.1 New media skills

Nowadays, technology in education is inevitable to achieve the mission of education, which is to educate people as members of society. “If it were possible to define generally the mission of education, it could be said that its fundamental purpose is to ensure that all students benefit from learning in ways that allow them to participate fully in public, community, [Creative] and economic life.” (New London Group, 2000, p. 9). Introducing technology to the learning environments requires students to have media literacy skills alongside traditional skills, such as research, technical, and critical analysis skills (Jenkins, 2006). Jenkins (2006) categorizes media literacy skills in 11 groups, including play, performance, simulation, appropriation, multitasking, distributed cognition, collective intelligence, judgment, transmedia navigation, networking, and negotiation. Dawson and Siemens (2014) name these skills as multiliteracies skills and indicate that the term multiliteracies is often used interchangeably with media literacies, digital literacies, or new literacies. These skills require new and diverse forms of assessment methods to be developed and implemented in education contexts.

2.1.2 Multiliteracies

The term Multiliteracies refers to two different aspects of language (Kalantzis, Cope, Chan, & Dalley-Trim, 2016). The first aspect is related to the variability of meaning-making in different social, cultural, or domain-specific contexts. These days, with the availability of being connected to people from other cultures and social groups, it is becoming more significant to value these differences in our communication environments. As a result, learning and teaching and the assessment in education cannot solely focus on the rules of particular national languages. The second aspect of multiliteracies refers to the characteristics of the information and communication media. Language and meaning-making are moving toward multimodal forms, where meaning-making is no longer restricted to text information. Instead, meaning-making is constructed through multimodal forms of information, including text, oral, audio, visual, video, gestural, and spatial patterns (Kalantzis et al., 2016). The term multiliteracies in my thesis refer to the second aspect of multiliteracies.

Multimodality in multiliteracies means extending the range of literacy pedagogy so that it does not solely include alphabetical forms of literacy but brings multimodal representations to learning environments, particularly those typical of digital media. Multimodality makes the literacy pedagogy more connected with today’s real-world communication media. The technological advancements, ease of access to information sources, and the emergence of new communication forms have changed the meaning of being literate in the 21st century. These changes have raised the discussions within educational research regarding the importance of developing multiliteracies skills in students (Haythornthwaite & Andrews, 2011).

2.1.3 Multiliteracies Assessment

In recent years, the importance of implementing multiliteracies' skills has led to the development of new assessment methods to measure these new media skills (Dawson & Siemens, 2014). Kerekes (2014) believes that assessment practices in learning settings require to be changed from individual, reading-writing, and print-based practices to ones that assess sociocultural dimensions of multiliteracies based on multimodal forms of data. Prior to multiliteracies assessment, researchers must determine which potential artifacts may be generated during learning and teaching; They also have to determine the possible assessment methods to evaluate these artifacts (Dawson & Siemens, 2014).

2.1.4 Multiliteracies Pedagogical Framework

Based on the framework proposed by the New London Group (1996), there are four key terms in Multiliteracies pedagogy, including situated practice, over instruction, critical framing, and transformed practice. These four components of pedagogy do not constitute a linear hierarchy nor represent stages. They may occur simultaneously and repeatedly revisited at different learning levels. These components are as follows:

1. Situated Practice is the component related to the immersion in the learning experience and the use of available learning content and designs of meaning. During the situated

phase, learners reflect on their own learning and familiar experience; also, they observe or take part in new content that is unfamiliar to them.

2. Overt Instruction is related to understanding designs of meaning and processes in a systematic and analytical way. Learners in this phase may group and categorize things or make generalizations using concepts.

3. Critical Framing refers to critically viewing the study topic in relation to the context of learning. In this phase, learners may analyze logical connections and interpret their own and other people's perspectives, motives, and interests.

4. Transformed Practice refers to putting the transformed meaning to other contexts. In this phase, learners may apply new learning to an actual situation, propose solutions, and test their validity. Also, learners can make an innovative or creative intervention in the real world.

2.2 Computational Thinking and Assessment

2.2.1 Computational thinking

Various studies in the literature provide different definitions for CT. Some studies define CT as a cognitive process, while others highlight it as a problem-solving approach (Zhang & Nouri, 2019). Also, CT definitions in the literature differ based on the goals, skills, and context of implementing CT (Tang, Yin, Lin, Hadad, & Zhai, 2020; Zhang & Nouri, 2019). Drawing from programming and computing concepts, many researchers defined CT as the process of programming, designing for usability, improving computational concepts, computational problem-solving, and system thinking. On the other hand, the definitions that emerged from CT's non-programming activities focus on CT's operational and real-life applications. The various definitions of CT have led to the emergence of different assessment tools and methods for the assessment of CT skills. Two next paragraphs provide a brief overview of the formation of CT definitions over time.

The term CT was first proposed by Papert (1996) in an article about mathematics education and defined as "procedural thinking." However, CT was not a topic of interest until Wing's (2006) study. Wing (2006) described CT as the approach to "solving problems, designing systems, and understanding human behaviour, by drawing on the concepts fundamental to computer science" (p. 33). Also, she stated that computational thinking is about conceptualization, not programming. Later, Guzdial (2008) mentioned CT as a problem-solving process that focuses on abstraction, evaluation, modelling and automation. With the rise in the importance of CT, the International Society for Technology in Education (ISTE) and the Computer Science Teacher Association (CSTA) offered an operational definition of CT as a problem-solving process that includes the following as its primary, but not all, characteristics: formulating problems in a way that can be solved by computational tools, logical thinking and analyzing data, representing data through abstractions, automating solutions through algorithmic thinking, and identifying, evaluating, and implementing possible solutions (Hershkovitz et al., 2019).

All the above definitions are common in that none of them explicitly mentions programming languages for CT acquisition. However, this is not a universal belief about CT. Brennan & Resnick (2012) stated that programming is essential in CT education. Their proposed theoretical framework presented three dimensions including, computational concepts (programming terms of sequences, loops, events, parallelism, conditionals, operators, and data flow), computational practices (iteration, debugging, and abstraction), and computational perspectives (expressing, questioning, and connecting). Another CT framework that originates from computational concepts is based on the study by Weintrop et al. (2016). The framework classifies CT into four dimensions: data practice, modeling and simulation, problem-solving, and system thinking. Since there is no unified CT definition, its definition and assessment methods change depending on the context (Kirwan, Costello, & Donlon, 2018).

2.2.2 Computational Thinking Assessment

The diversity in CT definition indicates the complex structure of CT (Allsop, 2019), and it is not possible to limit the CT assessment to one of the programming or non-programming constructs. The same as CT's definition, the assessment tools and techniques differ based on their various implementations. These assessment tools go further than evaluating the programming skills to perform assessment methods that assist students in the acquisition of problem-solving skills (Román-González, Pérez-González, Moreno-León, & Robles, 2018). Literature of CTA includes a wide range of different assessment techniques and methods, including qualitative, quantitative, and mixed-method approaches of evaluation (Weese, 2016a).

Although assessment is a core of learning, along with the CTA studies, there are various studies in the CT literature that ignore the assessment of CT skills. Also, many of the CT environments in k-12, are designed with focus on providing learners with an engaging experience of creating codes and computational artifacts and most of them ignore the assessment of learners' skills (Yadav et al., 2015). Without a proper and sufficient assessment, CT cannot expand in the k-12 education and move toward its vision (Grover et al., 2014). In CT education, the major goal of the assessment is to measure students' learning with the aim of improving their CT skills, not necessarily awarding student grades (Grover, 2017). Grover (2017) States that the result of CTA should highlight the gaps in students' CT understanding, and in turn informing enhancements to the curriculum and/or pedagogy.

Moreover, manually checking students' programming artifacts which refers to the traditional form of assessment, has some limitations in CTA. Although human-based assessment may better reflect students' learning in some concepts, this form of assessment can be subjective and time-consuming. There are automatic assessment tools such as Dr.Scratch that have addressed this issue of traditional assessment (Moreno et al., 2015; Srinivas et al., 2018). However, Brennan (2012) claims that the computational construct in students' coding structure does not necessarily show their real CT skills. In contrast, artifact-based interviews can provide a more clear picture of students' learning from the programming projects in different CT environments (Basogain et al., 2018; Weese, 2016). So, literature does not offer a unique assessment tool for CT skills. Moreover, while some of the presented assessment methods are valuable for research to provide a holistic view of learner's skill acquisition in CT, they may not be practical based on the current curriculum and pedagogy (Grover, 2017).

2.3 Learning Analytics for Learning Assessment

Exploring data science literature in education, we can pinpoint three closely related concepts, including learning analytics (LA), educational data mining (EDM), and academic analytics (AA). Although these fields have significant similarities in methodologies, techniques, goals, and target individuals, they are different in some dimensions, such as target stakeholders. AA refers to analyzing educational data to improve educational institutions' decision-making and performance (Ndukwe & Daniel, 2020). AA implements big data analysis techniques, statistics, and predictive modelling (Campbell et al., 2007) and focuses on decision-making in the upper layers of education taxonomy, such as the institutional layer.

Compared to AA, EDM and LA have more similarities. They both focus on the lower education taxonomy levels, such as individuals or schools. However, EDM and LA also have differences. Siemens & Baker (2012) present five differences between EDM and LA. 1) EDM and LA have different goals in knowledge discovery; While LA aims to leverage human judgment, in EDM leveraging human judgment is a tool. 2) EDM and LA have different origins. EDM focuses on student modelling based on educational software, but LA is about outcome prediction, intelligent curriculum, and systematic interventions. 3) LA and EDM employ different techniques and methods. EDM mainly relies on classification, clustering, Bayesian modelling, relationship mining, discovery with models, and visualization. In addition to these methods, LA includes other analysis techniques such as sentiment analysis, influence analysis, social/epistemic network analysis, success prediction, and sense-making analysis. 4) EDM performs automated personalization, while LA informs and provides guidelines for instructors and students. 5) EDM considers a system as a set of components and investigates the relationships between them, while LA aims to analyze the whole system. Since many studies refer to EDM and LA as interchangeable concepts, my thesis will explore both approaches as LA.

2.3.1 Learning Analytics: Theory and Definition

The Research Handbook of the Society of Learning Analytics (2017) states that "when Evidenced-Based Practice (EBP) and the three-legged stool of Epistemology, Pedagogy, and assessment are applied to LA, it takes LA from theory to practice" (Ochoa, 2017). The Epistemology-Pedagogy-Assessment (EPA) framework defines the relationships between its three elements. Applying EPA to LA means assessing learners' performance based on pedagogical feedback and epistemological views (Knight et al., 2014). Moreover, applying EBP to LA refers to providing evidence to reject or support educational data analysis findings. Romero (2010) states that EBP is about information retrieval, organization, and management of the analysis results to provide daily decision-making information.

Based on the relation between EPA and LA, LA refers to collecting the data related to pedagogy and epistemology to assess learning environments and students' performance (Adeniji, 2019); and this process aims to provide the required information for improvement and decision making in educational settings. The most popular definition of learning analytics in literature was presented in the First Learning Analytics and Knowledge Conference in 2011. Siemens et al. (2011) stated that "learning analytics is the collection, measurement, analysis, and reporting of educational data, including data about learners, and their context, for understanding and enhancing learning and the environment in which it occurs." Although the definition includes the main concepts in LA, it is too general to highlight different aspects of LA's current trend.

2.3.2 Learning Analytics: Dimensions

Chatti et al. (2012) presented a model that highlights four questions about LA, including why to use LA (purpose), what type of data to analyze (data), how to perform the analysis (method and techniques), and who are the stakeholders. These four dimensions are discussed in the following. Except for these four dimensions, some other scholars added two extra dimensions, including internal limitations and external constraints (Greller et al., 2012).

Learning Analytics: Purpose. Various scholars mentioned assessment and educational decision-making as the main goals of LA (Derick et al., 2017; Mangaroska et al., 2019; Millecamp et al., 2018). However, other scholars believe that LA is more a tool to assist learning than a means to assess it. Blikstein (2016, p.221) states that “an important goal of learning analytics is to equalize the playing field by developing methods that examine and quantify non-standardized forms of learning.” Based on (Cukurova et al., 2016), learning analytics is an effective way of supporting learning activities rather than being a measure of determination. From this perspective, LA is a tool to “*augment human intellect*” rather than measure it. According to the finding of a literature review by Moissa et al. (2015), LA is generally done with one of the following purposes: adaptation, evaluation and feedback, monitoring and analysis, personalization and recommendation, prediction and intervention, reflection, mentoring, and tutoring.

Learning Analytics: Data. The data source for LA can be from various sources, including virtual learning environments, social networks, surveys, digital libraries, or other repositories. Also, LA utilizes various forms of data, including click-stream and log-based data, text, handwriting, sketch, speech, programming artifacts, gaze data, affective state and emotion, action, and gesture (Mangaroska et al., 2018; Martinez-Maldonado et al., 2018; Mitri et al., 2019; Williamson, 2017; Worsley et al., 2010). Some studies have used triangulation of data to improve the findings; for example, Blikstein (2016) combines speech recognition with handwriting to analyze the duration of time students need to complete tutoring activities.

Learning Analytics: Method and Techniques. Aiming to achieve the LA objectives, previous studies have used different methods such as clustering, classification, regression, statistics, text mining, sentiment analysis, visualization techniques, and social network analysis (Vieira et al., 2018).

Learning Analytics: Stakeholders. Different individuals in learning environments could benefit from LA. Banihashem et al. (2018) categorized the benefits of learning analytics based on various stakeholders. These benefits and their associated stakeholders are as follows:

1. Learners: The first benefit of LA for learners is the enhancement of their engagement and learning outcomes. Personalization of learning processes and learning environment is another benefit of LA for students. Finally, LA can be used to increase self-reflection and self-awareness.

2. Teachers: LA could provide effective assessment services, real-time feedback, monitor students' activities, and help teachers better understand students' learning habits. Moreover, LA can recommend study material or teaching strategies to improve instructors' performance. Finally, LA can be used to predict and provide warning signals for teachers.

3. Institutions: improved educational decision-making, boosted cost-efficiency, increased students' return rate, increased student success are some of the possible benefits of LA for institutions. Also, LA assists institutions in curriculum improvement and making evidence-based decisions.

4. Researchers: Using LA in education helps researchers measure and enhance education efficiency and find knowledge gaps.

5. Course Designers: LA could benefit course designers by identifying target courses and improving learning design.

6. Parents: Using the results from LA, parents can monitor students' activities and outcomes.

2.3.3 Learning Analytics and Big Data

The current tendency in LA refers to the analysis of data gathered from user activity. More importantly, this data is not restricted to online learning environments like LMSs. It may also include data from different sensors that can be used in physical or online learning settings. Besides, educational data are created by institutions that use specific applications to manage courses, learning materials, and students (Sin et al., 2015). The large volume of data extracted from all these platforms and devices leads to a significant information source that can help education stakeholders improve the learning experience and outcomes (Cantabella et al., 2019). However, due to the high volume and complexity of these data, they cannot be easily analyzed by traditional data analysis techniques (Sin et al., 2015). Due to these limitations, institutions and researchers started to use big data techniques for analyzing educational data.

Cantabella et al. (2019) state that while implementing big data in LA helps educators and learners improve the learning process, big data has some disadvantages. Big data include large datasets with various formats and structures that make big data management and analysis more complicated than analyzing traditional data forms. Moreover, in some educational environments, such as mobile learning, where mobile devices have lower processing capabilities, implementing big data is more challenging (Shorfuzzaman et al., 2019). Sin et al. (2015) summarize the challenges of handling big data in three main categories: storage, analysis, and reporting.

Different studies have developed big data frameworks to harness the use of big data in LA. Shorfuzzaman et al. (2019) introduce cloud computing as a solution for big data analysis in mobile learning. Cantabella et al. (2019) use Hadoop in their big data framework for analyzing the data in a learning management system. Moreover, different technologies and tools have been introduced for big data storage, analysis, and reporting; MongoDB, Hadoop, MapReduce, and Weka are among the big data analysis tools discussed in the literature (Sin et al., 2015).

2.3.4 Multimodal Learning Analytics

Multimodal Learning Analytics (MMLA) refers to the use of learning analytics with multimodal forms of data. Blikstein (2016) defines MMLA as "a set of techniques employing multiple sources of data (video, logs, text, artifacts, audio, gestures, biosensors) to examine learning in realistic, ecologically valid, social, mixed-media learning environments." Worsley (2014) states that MMLA includes applying analytics and data-mining techniques in constructionist and open-ended multimodal learning environments. Based on Worsley's (2014) study, the objective in MMLA is to track learning by collecting and analyzing data from multiple modalities and finding the connection between complex learning behaviours, learning strategies and learning theories. However, MMLA is an emerging field, and more research is needed to reveal its different aspects; for example, a survey on MMLA showed that about fifty percent of the eighty-two analyzed papers were theoretical research (Worsley, 2018).

2.3.4.1 Categories of Multimodal Learning Analytics

Different categories of MMLA are as follows.

1. Text Analysis. Any kind of text data in educational environments could be used in LA. Open-ended writing tasks, open-ended questions, face-to-face and online activities, online sources, policy documents, textbooks, and exams can be used as text data sources in LA (Blikstein et al., 2016). The advantage of text analysis is the possibility of large scale analysis of text databases. Except for text data, learners' programming artifacts can also be used as data in LA to assess individuals' coding skills (Blikstein et al., 2014).

2. Speech Analysis. Analyzing speech compared to text data has advantages. First, the possibility of analyzing speech opens new rooms for implementing learning analytics in a non-traditional learning setting, where the assessment is no longer restricted to exams and text. Second, by analyzing the speaker's tone and voice, speech analysis can perform more accurate analysis than text analysis (Dawson et al., 2014). Worsley (2011) conducted a speech analysis to identify expertise in students. The study shows that the speech patterns in expert and novice students are different. For example, the average duration of novice students' responses to questions was twice the time for expert students. Moreover, another study of Worsley & Blikstein (2013) showed that the key markers of learners' expertise include user certainty and the ability to describe

things effectively. Their study analyzed students' performance based on these metrics.

3. Handwriting and Sketch Analysis. The use of handwriting and sketch in LA can broaden LA's scope beyond the traditional forms of data, including keyboard and mouse-based entries. These two forms of analysis can extend LA to early childhood learning, and those learning environments that text data is not available. Different studies have used computer vision or intelligent boards, and machine learning to analyze learners' handwriting or drawings (Schick et al., 2012). Moreover, sketch analysis provides the possibilities of analyzing diagrams and figures, which are the new forms of education in STEM education (Blikstein et al., 2016).

4. Gesture and Physical State Analysis. Gesture or action analysis includes the techniques that capture learners' actions, independent of their personal characteristics such as body size and gender. These analyses can be used to capture individuals' engagement and attention by analysis of video frames. Moreover, action analysis can support immediate feedback on the correctness of students' movements, such as hand placement or their body movements in sports education (Martinez-Maldonado et al., 2018). The use of specific sensors or technologies can even broader the form of information extracted from the gesture analysis; for example, infrared cameras avoid some of the complexities of regular cameras (Schlömer et al., 2008). Martinez-Maldonado et al. (2018) use the concept of distributed cognition theory, Internet of things, and LA to provide a theoretical framework for the analysis of the learning process in physical spaces; The study uses motion, proximity and location sensors for the aim of physical learning analysis.

5. Affective State Analysis. Analyzing students' affective state relies on one or more of the possible data sets for identifying individuals' affective state, including text, speech, action logs, interaction with other learners and environment, and facial detection (Derick et al., 2017; Schneider et al., 2015). Besides, using different educational theories, studies in the literature select various affective states for their analysis. For example, Mello (2014) Selected anger, anxiety, boredom, confusion, curiosity, fear, engagement, happiness, and frustration. The study investigates how the interaction of various events lead to selected affective states, and how those affective states trigger learners' behaviours.

6. Eye Gaze Analysis. Eye gaze is one of the important indicators of attention. Several studies indicated that students' performance correlates with their eye gaze pattern regarding the directions and duration of the learners' look (Blikstein et al., 2016). Gomes et al. (2013) studied eye-tracking analysis to provide positive intervention in STEM education. Besides eye gaze data, they also collected data from mouse clicks and the learning task's duration to better predict the students' performance. Mangaroska et al. (2018) predict students' expertise in programming based on their gaze pattern. The analysis results indicate that learners' coding expertise positively correlates with success in debugging, a metric associated with the gaze pattern.

2.3.5 Visualization and Reporting Learning Analytics

The results from LA could be reported in both text and visual formats. However, visualization in LA is both a technique for reporting and analysis and as mentioned earlier, we know that leveraging human judgment is an aim in LA. So, visualization can provide a model to facilitate understanding data in context (Mangaroska et al., 2019). Visual data analysis refers to graphics and computational methods to extract patterns from large datasets and present them in visualization tools. Different websites and tools can be used to create visualizations; Gapminder, IBM Many Eyes, and FlowingData are among the tools for big data visualization (Avella et al., 2016).

Chapter 3

3 Methodology

The proposed research is designed as two systematic literature reviews in CTA and LA. This systematic literature review approach uses machine learning techniques for data-driven content analysis and uses qualitative analysis to support the data-driven literature review.

3.1 Systematic Data-Driven Literature Review

The literature review on the two articles of this thesis aims to combine the strengths of qualitative and quantitative content analysis methods (Hong et al., 2017). Ananiadou et al. (2009) state that it is required to harness the powerful text-mining[1] technologies in SLRs to deal with the rapid growth of research literature in different fields. Although quantitative methods can meet the requirements of systematic literature reviews for large datasets, they demand high recall for SLR studies, which is not always applicable (O'Mara-Eves et al., 2015). On the other hand, even though qualitative literature review methods have limitations regarding the size of the dataset, they can provide for in-depth analysis of literature (Gough, 2015). As a result, this thesis has conducted a quantitative systematic literature review supported by a qualitative study of selected literature items.

[1] The automatic process of deriving valuable information from unstructured text using quantitative techniques

The stages of the systematic review in this thesis are based on the guideline in Pluye's (2014) and Kitchenham's (2007) research. Figure 2 represents these stages which are also discussed in the following.

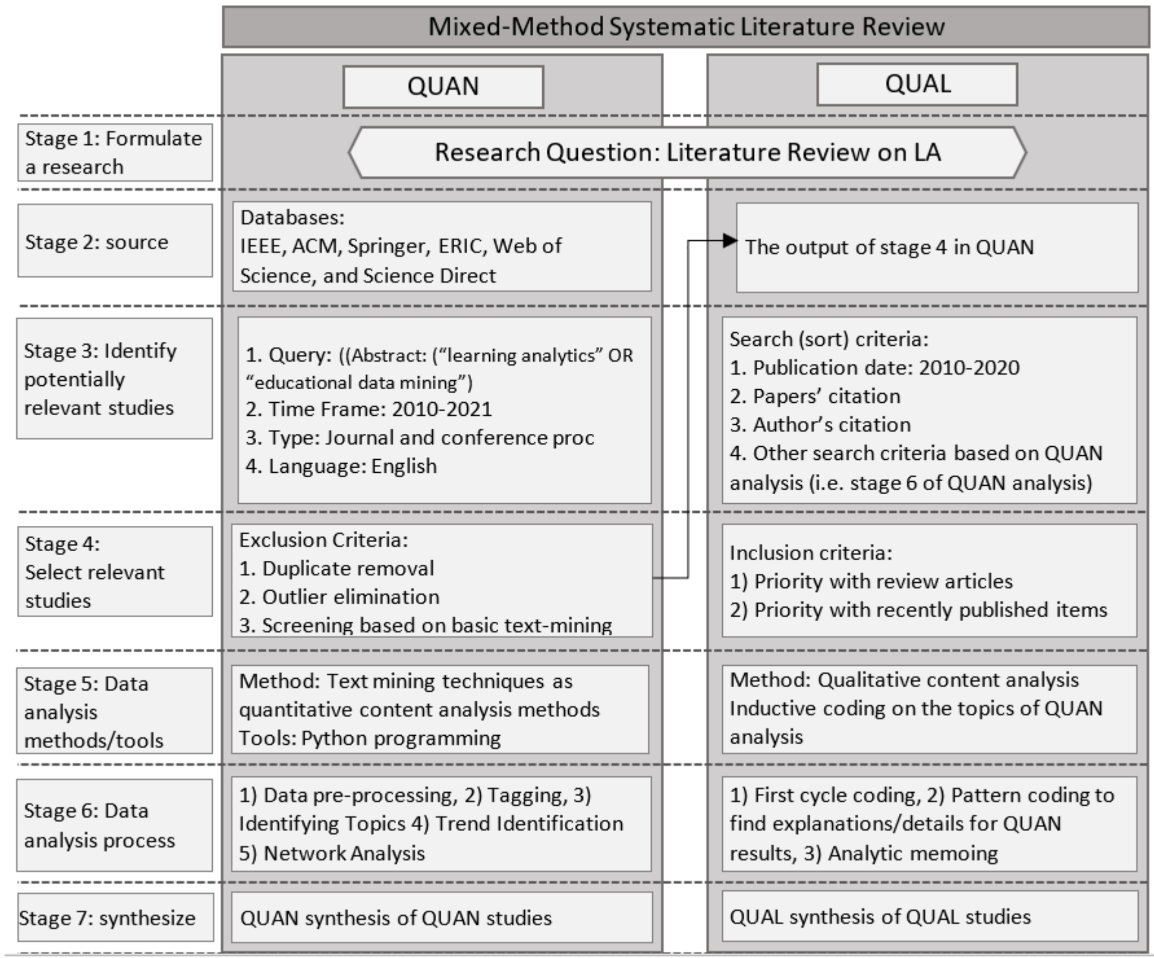

Figure 2 The stages of the systematic literature review in the two studies of the thesis

3.1.1 Stage 1: Formulating a Research Question

In the first article, the research questions for both quantitative and qualitative methods are the same. The quantitative results will be followed by qualitative analysis to provide further explanations.

3.1.2 Stage 2: Information Source

The literature documents were collected from different scientific databases, including ACM, IEEE, ScienceDirect, Web of Science, ERIC, and Springer. The literature items for the qualitative analysis include a subset of articles from quantitative analysis.

3.1.3 Stage 3: Search Strategy

We have used specific queries for each study to collect the text data. The collected data includes peer-reviewed English journals and conference papers published after 2010. We used text analysis methods, including word frequencies and clustering, to identify keywords in each study and improve the queries during the pilot studies.

The search strategy for qualitative analysis is to look for the recent or literature review items selected from the dataset for quantitative analysis. Also, different factors such as cite scores of research items, recent papers of highly cited authors, and the results from the quantitative analysis have been used to select the literature items for the qualitative analysis.

3.1.4 Stage 4: Selection Strategy

The quantitative analysis was conducted on selected documents' titles, abstracts, and keywords. This stage included removing duplicates and outliers based on word similarity measures (Nasar et al., 2019). Also, we used basic text mining methods from Feng et al. (2017) for screening. The screening process included deleting the documents containing non-relevant top keywords to the topic of study with this assumption that similar documents share similar words (Ananiadou et al., 2009). The text analysis methods utilized in stage 4 are as follows: First, we identified duplicate items using similarity measures popular in quantitative text analysis, such as cosine similarity. Second, we eliminated outliers using similarity measures. Outliers in our study were considered those documents with significantly low similarity to the other retrieved documents from stage 3. To find outliers, we calculated average similarity of each document to other documents and eliminated the documents with significantly low average similarity to other documents of the dataset.

3.1.5 Stage 5 and 6: Data Analysis Method and Process

For the aim of our data-driven literature review, we used NLP techniques for pre-processing of the selected documents. We used topic-modelling, an automatic text mining approach that can be utilized for systematic literature reviews (Feng et al., 2017). Topic modelling is a technique that automatically assigns documents to different categories based on the content of documents (Ananiadou et al., 2009). Also, we implemented a network analysis to explore the connections between the identified topics. The process for stage 5, data analysis methods, and stage 6, data analysis process, are as follows.

Stage 5 is related to the identification of text analysis methods. We used different Natural Language Processing (NLP) tools in python to perform the pre-processing of the text documents before finding the topics. Second, we used topic modelling based on Latent Dirichlet Allocation(LDA) algorithm to identify the latent topics in the literature. We also utilized Social Network Analysis (SNA) to identify the topic connections using python libraries. Finally, We used Factor Analysis on the top keywords of the topics to identify the most important keywords that define their corresponding literature.

Stage 6 is related to the implementation of the selected analysis methods. In the following, each of the data analysis phases, including pre-processing, topic-modelling, network analysis, and factor analysis, are discussed. The corresponding examples are from the first study of the thesis. The second study has the same process.

3.1.5.1 Pre-processing of the Selected Literature Items

Pre-processing refers to the process of selecting relevant word-features and preparing meaningful data for the data analysis step. We performed multiple pilot studies on smaller literature datasets for each of the two articles. We developed an effective way to find a “core vector space” for each article based on the pilot studies. A core vector space (CSV) in text analysis is a dataset version without nonrelevant or nonimportant word-features. We identified the CSV in three steps as follows: duplicate and outlier removal, cleaning the database by eliminating symbols, numbers, lowercasing, normalization of words (e.g. “assessment” and “evaluation” has the same meaning), stopword removal (e.g. “and”, “is”), lemmatization (e.g. “computing” to “compute”), deleting context-related words repeated in a significant number of documents (e.g. “learning” and “student” in CTA context), and deleting document specific words such as abbreviations, finally, checking and deleting outliers in the pre-processed database.

Figure 3 illustrates the process for finding a CSV. The black cells indicate that the corresponding word (column) appears in which document (row).

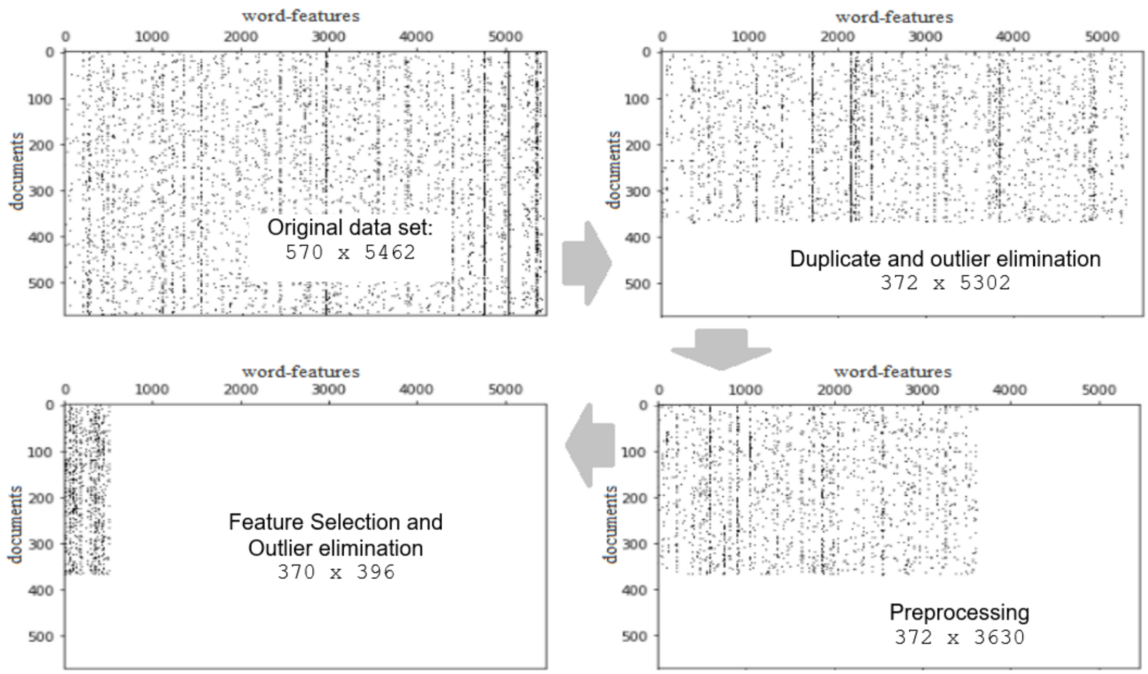

Figure 3: The process of finding a Core Vector Space

3.1.5.2 Identifying Topics

Identifying topics is named topics modelling and refers to using unsupervised machine learning techniques to find the topics in a database of documents. In this thesis, we used Latent Dirichlet Algorithm (LDA) to identify LA and CTA literature topics. LDA is an unsupervised machine learning technique for identifying latent categories in a dataset. We used python programming language and Gensim library to implement LDA. Even though LDA is an unsupervised machine learning algorithm, it must be given the number of topics as a parameter. There are various methods to solve this problem and automatically find the optimal number of topics. We used four metrics, including Arun2010, CaoJuan2009, Deveaud2014, and Griffiths2004. The following paragraphs provide an overview of these four metrics.

Arun2010 metric (Arun, Suresh, Veni Madhavan, & Narasimha Murthy, 2010) aims to find the optimal number of topics by minimizing the distance between different Document-Topic and Topic-Word matrixes distributions. CaoJuan2009 method (Cao, Xia, Li, Zhang, & Tang, 2009) claims that the LDA model performs better when the average cosine distance of topics is the minimum; as a result, it aims to minimize the average distance of topics. Deveaud2014 metric (Deveaud, SanJuan, & Bellot, 2014) finds the optimal number of LDA topics by maximizing the information divergent between all topics in an LDA model. Finally, Griffiths2004 (Griffiths & Steyvers, 2004) uses the Bayesian model selection to find the number of topics. The rationale behind this method is to maximize the probability of selecting a word when it appears in specific documents and topics.

Figure 4 shows a sample result from these four metrics for identifying the optimal number of topics in the CTA Literature review in chapter 5. Since these four metrics measure the dataset's different characteristics, the y-axis in Figure 4 does not have a label, and we have normalized the results to the 0-1 range. After using the above metrics to find the optimal number of topics, we manually reviewed the results for different topics numbers in both articles to select the most meaningful number of topics. Finally, the selected number of topics was used as a parameter for the LDA method to identify literature topics.

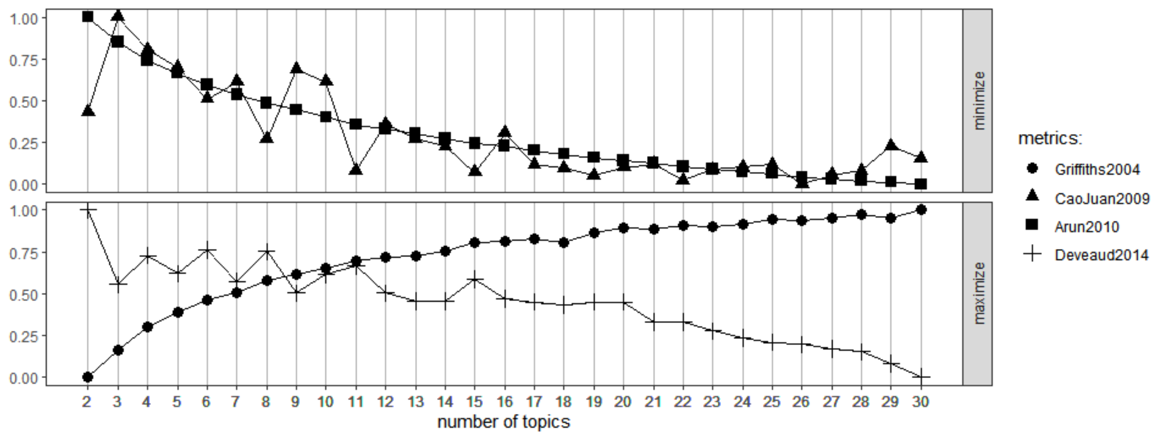

Figure 4: A sample results from the four metrics used for identifying an optimal number of topics for LDA

3.1.5.3 Network Analysis

In both articles of this thesis, topic modelling follows with network analysis of the identified topics. Network analysis is a method to explore the interconnection of a group of items based on their similarity. Network analysis shows the items as nodes of a network and their connections as edges that connect the network nodes. Regarding topic modelling in this thesis, topic similarity means the number of the same keywords between any pair of topics. If there are a significant number of common keywords between two topics, the corresponding nodes of those topics will be connected on the network of topics. Topics with more similarity to the other topics form the most connected nodes of a network of topics. Network analysis can be used to further interpret the single topics, their interconnections, and the literature as a whole.

3.1.6 Stage 7: Synthesis

Finally, the results from the quantitative analysis were synthesized and supported by qualitative analysis to answer the research questions.

Chapter 4

4 Data Analytics in Education: A Data-Driven Literature Review

In the past decade, the applications of learning analytics in education have made significant headways. This advancement highlights the new opportunities for educational analytics, prediction, and decision-making. However, the combination of big data and quantitative analysis has brought new challenges to academic analytics. This paper focuses on developing a systematic data-driven Literature review of big data analytics in education. This study identifies the key topics of big data analytics in education and investigates the possible reasons for the issues and challenges in that field. The study utilizes a machine-learning approach to explore the key themes. We have identified six topics and 19 subtopics using the Latent Dirichlet Allocation topic modelling. We also performed a network analysis to explore the links between the topics. Based on the analysis results, the study presents a three-dimensional model for big data analysis in education and describes how this model and challenges in educational data analysis are related. The paper provides recommendations for future research.

4.1 Introduction

The advancement of technology and the use of learning analytics to analyze educational data have provided the opportunity to store, track, evaluate, and visualize students' learning in large datasets (Avella, Kanai, & Kebritchi, 2016). Even though most big data analysis (BDA) in education refers to online settings, such as learning management systems (LMS), the use of new technologies provides the possibility of tracking students' learning in a broader range of environments and data formats (Klašnja-Milićević, Ivanović, & Budimac, 2017). The development of big data applications in education has brought new benefits to enhance teaching and learning. It also introduces new issues and challenges in different aspects (Daniel, 2019).

“Big data” refers to any dataset that is too large or too complex to be computed by conventional applications (Sin & Muthu, 2015). The data can also be structured or unstructured and presented at any speed, such as real-time. Big data is generally categorized into three Vs, including Volume, Variety, and Velocity (Shorfuzzaman, Hossain, Nazir, Muhammad, & Alamri, 2019). With the characteristics of big data methods and techniques, big data can enhance complex educational data analytics.

Learning analytics (LA), educational data mining (EDM), and academic analytics (AA) are three closely related concepts (Siemens & Baker, 2012). However, they have some differences in their scopes and methods. Using machine learning and predictive modelling, LA provides actionable information. LA mainly focuses on individual users’ needs, such as early prediction of academic success to allow teacher intervention in students’ learning processes. EDM uses data-mining methods to promote discoveries in educational settings (Avella, Kanai, & Kebritchi, 2016). Finally, AA involves business intelligence techniques and mainly focuses on the organizational level. Researchers believe that these three related subjects overlap in the definition and scope (Doleck, Lemay, Basnet, & Bazelais, 2020).

In the past decade, there have been several studies on big data in education to enhance the information discovery in administration, student/learning, and teaching/delivery aspects. However, since the nature of BDA is different from traditional quantitative or qualitative analysis, the current state of it in education is still far from fulfilling the information discovery needs. More importantly, the sensitivity of educational environments adds more complexity to BDA in learning settings.

This study aims to perform a data-driven literature review to discover the themes in educational BDA literature. Focusing on the challenges in that field, we aim to investigate how the existing body of literature responds to the needs in the big data area in education, what challenges are remaining, and which aspects require further research. Various studies have addressed current challenges and issues in BDA. They mainly focus on privacy, ethical issues (Avella, Kanai, & Kebritchi, 2016), and technical limitations (Otoo-Arthur & Van Zyl, 2019). We believe that the challenges in BDA might go beyond that.

4.2 Challenges and issues of big data analytics in educational research

Some studies in the literature of BDA have categorized the potential challenge and issues as follows (Daniel, 2019):

- Technical Issues: These issues include handling a massive amount of data, protecting privacy through authentication, and the limitations of predictive methods to model the complexity of educational settings.
- Ontological Issues: in the education field, researchers infer the information based on the context. A critical part of educational research is engaging with the data collection process, while in BDA, the researcher is rarely involved in data collection.
- Epistemological Issues: due to the complexity and dynamicity of data, BDA is different from the previously known quantitative, qualitative, and mixed-method research methodologies.

- Data Analysis Issues: The predictive and analysis methods in BDA are useful for answering “what” rather than “why” questions. While in education, we often need to provide reasons.
- Digital Divide Issues: BDA requires the involvement of data scientists; however, there are not many of them working in the education field.
- Privacy and Ethical Issues: On the one hand, maintaining confidentiality and ethics in education has its challenge, and on the other hand, preserving privacy limits the possible applications of BDA.

4.3 Method

Aiming to identify the topics of “big data in education,” we relied on a systematic literature review and Latent Dirichlet Allocation (LDA) as a topic modelling approach. LDA is an unsupervised machine learning technique to discover latent categories of a dataset (Deveaud, SanJuan, & Bellot, 2014).

4.3.1 Data Collection

We collected the text data of scientific publications from six databases, including ACM, IEEE, Scopus, Web of Science, Springer, and ScienceDirect. The collected data included title, abstract, and keywords of journal articles and proceeding papers related to “Big Data Analysis in Education.” Considering 2010 as the first year that big data analytics was introduced to the education field, we retrieved studies since 2010. The query used for data collection was {Topic: ((“learning analytics” OR “educational data mining” OR “academic analytics”) AND (“big data” OR “large data”)}. The word “Topic” in the search query refers to the articles’ metadata, including title, abstract, and keywords.

4.3.2 Data Selection

Since review studies do not concentrate on a single topic, we excluded them. Also, we removed the duplicates from the search results. The remaining was 527 documents. Table 1. shows the number of search results from each dataset.

Table 1: Overview of Data Collection

Data Source	Number of Search Results
ACM	27
Web of Science	328
IEEE	155
Scopus	385
ScienceDirect	16
Springer	68
Total	979

4.3.3 Data preprocessing

Preprocessing of data includes the process of identifying a collection of meaningful word-features; this collection is called core vector space (CVS). Our original selected dataset included 527 articles with a total of 5,206 features. We performed cosine-similarity and Jaccard coefficient based on tfidf vectors for outlier removal, and we performed data cleaning and feature selection to find a homogenous CVS for the dataset. The first step of preprocessing included the following techniques: stop word elimination, lowercasing, number and punctuation removal, bigram and 3-gram processing, normalization, and lemmatization. During the preprocessing, we used the following python libraries: nltk, gensim, spacy, and sklearn.

In the second preprocessing step, we used CountVectorizer and TfidfVectorizer from the sklearn python package to select relevant word-features considering both tfidf and frequency-based analysis. The words that appeared less than two times in the dataset were deleted. tfidf values were used to exclude document-specific words such as acronyms. The high-frequency words that can be found in scientific data (e.g., "aim," "research," and "analyze") and general English (e.g., "however" and "may") were deleted. Since such word-features have low tfidf scores, we identified them based on their tfidf scores. The preprocessing resulted in a CVS with 490 articles and 426 word-features.

4.3.4 Data Analysis

We performed LDA topic modeling to analyze the CVS and used network analysis of the identified topics to explore their connection. We used python's genism package to implement LDA. Even though LDA is an unsupervised machine learning algorithm, it requires the number of topics as the input value. We used Arun2010 and CaoJuan2009 metrics and coherence score. Arun2010 (Arun, 2010) finds the optimal number of topics by minimizing the distance between different Document-Topic and Topic-Word matrixes distributions. CaoJuan2009 method (CaoJuan, 2009) claims that the LDA model performs better when the average cosine distance of clusters is the minimum. Since the metric for finding the optimal number of topics does not guarantee good results for human interpretation, we manually reviewed the results for different topic numbers. Finally, six topics and 19 subtopics were selected.

We used an adjacency matrix (Longabaugh, 2012) to visualize the results from topic modelling. Fig. 1 shows a binary adjacency matrix for the dataset documents. The black cells mean that the similarity between the two corresponding documents is higher than the average similarity in the CVS. Also, each of the borders represents a topic of documents. Each topic's size shows the number of documents within that topic, and the density means homogeneity of each topic. For interpreting and naming the identified cluster, we considered both sizes and densities of the topics.

4.4 Results

4.4.1 Big Data in Learning Analytics: Topics

Figure 5 shows six research topics of “Big data in Learning Analytics” identified from the LDA algorithm. Also, we identified 19 sub-topics within these six topics. The following paragraphs of this section describe the topics and an example of their related studies. The sample studies for each topic are among the top ten documents of the corresponding cluster from topic modelling.

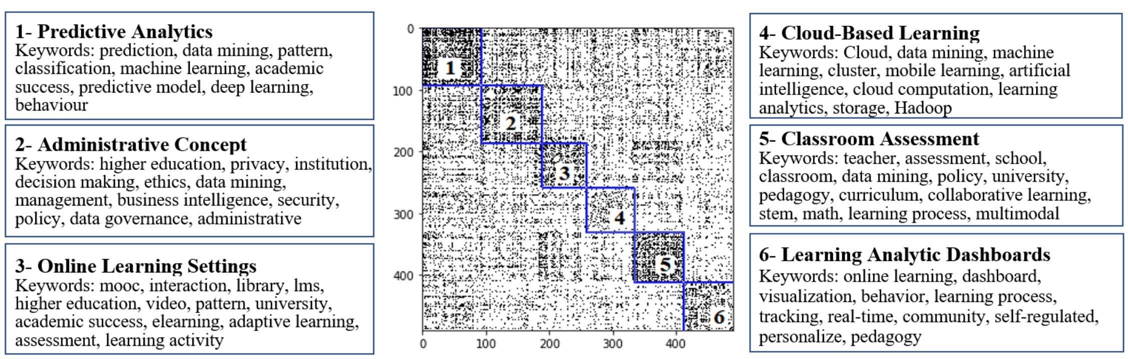

Figure 5. Six research topics of big data analytics in education

4.4.1.1 Topic 1: Predictive Analytics

Topic 1 is related to methods and algorithms used to predict different concepts in educational settings, such as students’ success rates. Pattern discovery and classification of learning activities are also included in this topic. This topic generally refers to the computer science aspect of big data in LA and consists of the following sub-topics.

1. Supervised Learning Methods: several studies used supervised learning and neural networks to predict students' learning, such as predicting students' drop-out rate with supervised learning (Santos, Menezes, Carvalho, & Montesco, 2019).

2. Academic success prediction: different studies have used historical grade data to create a prediction model for students' grades (Sweeney, Lester, & Rangwala, 2015).

3. Behaviour Prediction: Big data provides the opportunity for collecting and analyzing various data formats. Some studies examined learners' activities in the educational environments and predicted their behaviour (Alloghani et al., 2018).

4.4.1.2 Topic 2: Administrative Concepts

This topic refers to managerial concepts, institutions, decision-making, and other relevant concepts. The topic includes four subtopics, and most of the studies are related to higher education.

4. Policies: This subtopic addresses institutional and federal policies related to the use of BDA in education. The necessity of data privacy, its limitations for BDA, and possible solutions are discussed in the related studies (Howell, Roberts, Seaman, & Gibson, 2018).

5. Decision-Making: the results from BDA can support the decision-making process to improve education quality (Khanna, Singh, & Alam, 2016).

6. Knowledge Management: the use of BDA at the governance level requires organized data flow. Data warehouse design, enterprise architecture, and

knowledge management frameworks are related concepts to this topic (Moscoso-Zea, Andres-Sampedro, & Luján-Mora, 2016).

7. Student Retention: Using BDA to analyze students' attitudes and behavior to increase student retention is discussed in this subtopic (Riffai, Duncan, Edgar, & Al-Bulushi, 2016).

4.4.1.3 Topic 3: eLearning Platforms

This topic addresses online and technology-enhanced learning environments, such as LMSs, massive open online courses (MOOC), video-based learning, and libraries that use data analysis techniques.

8. Learning Environments: Online learning can occur in learning management systems (LMA), course management systems (CMS), forums, social networks, and other online collaborative learning environments.

9. Benefit and Possibilities: personalized learning, availability of various data formats (e.g., video-based learning), and resources (e.g., digital libraries) are among the most significant differences between online and traditional learning.

10. Design: BDA can help to make efficient decisions in designing educational environments. For example, (Liu, Li, Pan, & Pan, 2019) used students' behaviour patterns to implement better learning games.

4.4.1.4 Topic 4: Cloud-Based eLearning

This topic includes cloud computing and data analysis of cloud data for eLearning purposes.

11. Learner tracking and modelling: the most significant advantage of cloud-based learning is that it provides the opportunity to collect learners' data from multiple sources. This research topic mainly focuses on student modelling to assist students in reflecting on their core competencies (Chou et al., 2017).

12. Smart Services: The use of smart systems and smart learning analytics can improve the effectiveness of analysis. Reference (Chou et al., 2017) utilizes an internet of things (IoT) framework to enhance analysis effectiveness.

4.4.1.5 Topic 5: Learning and Teaching

Topic 5 addresses analysis of learning processes, formative assessment, and concepts related to curriculum and pedagogy. This topic aims to provide useful information for teacher interventions.

13. Discourse Analysis: discourse analysis in social and collaborative learning environments reveals students' attitudes, satisfaction, and sentiment (Elia, Solazzo, Lorenzo, & Passiante, 2018).

14. Teacher Intervention: the use of analytics to detect and notify the teacher can facilitate learning for those students who need special attention (Ho & Shim, 2018)

15. Pedagogy: studies in this sub-topic refer to pedagogical supports provided in different platforms, BDA for pedagogical design (Wong & Li, 2016), and pattern visualization to assist teachers in evaluating the teaching and learning process (Larionova, Brown, & Lally, 2019).

16. Multimodal Learning Analytics: multimodal learning analytics can support the analysis of complex, hands-on, and open-ended learning experiences. For example,

Reference (Thompson, 2013) uses speech patterns to predict students' answers' validity.

17. Personalized Learning: personalization of learning refers to accessibility to individualized knowledge to enhance the learning process. Providing personalized reports for teacher intervention, adapting the learning environment, or personalized dashboards are examples of related research (Farahmand, Dewan, & Lin, 2020).

4.4.1.6 Topic 6: Learning Analytics Dashboards

Topic 6 refers to data visualization and Learning analytic dashboard (LAD). This topic includes all education stakeholders, including learners, educators, and institutions.

1. Stakeholders: different individuals in an educational system can use lADs. Students may use them for self-regulated learning, teachers utilize LADs to monitor students' learning, and institutions can utilize them for decision-making (Shankar et al., 2020).

2. Applications: dashboards and visualizations represent knowledge discovered from data analysis and are used for different purposes such as monitoring, assessment, motivation, self-regulation, and policymaking (Farahmand et al., 2020).

4.4.2 Network Analysis of Identified Topics

The above results show that the six identified topics are highly related and have similar concepts. Figure 6 illustrates a network of six research topics and their relationship. Each topic is connected to at least two other most similar topics based on cosine similarity values. As Figure 6 shows "eLearning Platforms" topic is the most connected node of the network.

4.5 Discussion

The six identified topics can be categorized into three groups: theoretical, technological, and management. Each of the six topics and their 19 subtopics fits in one or more of these three categories. For example, “topic 1; predictive analytics” is in the intersection of theoretical and technical categories, and “topic 2: administrative concepts” is related to technical and management categories. We believe that the challenge and issues in educational big data roots in ignoring the intertwined connection of these three categories presented in Figure 7. As an instance, the complexity of education fields requires data analysis algorithms to consider the pedagogical and theoretical concepts in their analysis. Overlooking them may lead to data analysis algorithms that provide unrealistic or nonapplicable results from the learning environments. Other studies as well mentioned similar categories. Reference (Luan et al., 2020) states that big data and artificial intelligence develop at the intersection between policy, research, and industry. As Luan et al. (2020) mention, development in the intersection of research and industry leads to technical advancements, such as big data processing techniques in education. Also, advancement in the intersection of research and policy provides solutions for privacy issues. Finally, development in the intersection of policy and industry improves data and privacy protection.

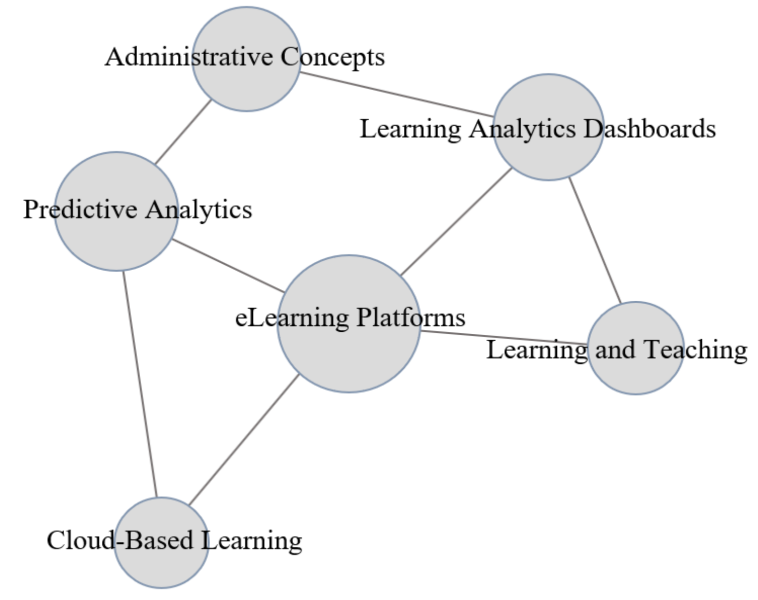

Figure 6. A network of research topics in educational big data analytics

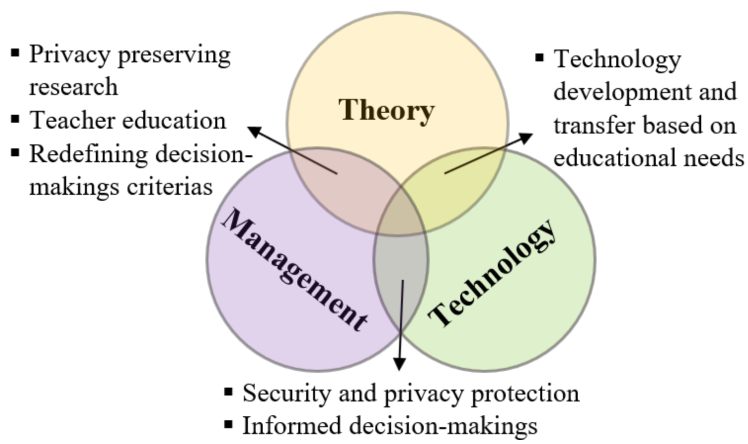

Figure 7. A three-dimensional model of categories in big data and learning analytics research

As Figure 7 illustrates, these three domains of theory, management, and technology would lead to BDA improvements in education when they are interconnected. More importantly, improvements in each of them may provide solutions for other categories. For example, ethical issues from the policy category can be solved by advancements in the technology category, and predictive algorithms can be improved by implementing pedagogical considerations.

Moreover, educational researchers have to consider a broad range of issues while working with big data analytics (Daniel, 2019). Reference (Daniel, 2019) mentions that educational big data issues might be in one of the following dimensions: conception, technical, epistemology, ontology, methods, digital divide, ethics, and privacy. Mapping the previous studies and identified topics to these seven issues provides a better understanding of existing studies' applicability.

Based on the existing big data analysis techniques achieving privacy requirements might be difficult. For instance, Hadoop is designed to work with public data, so it does not have enough security to be used in educational analyses (Quadir, Chen, & Isaias, 2020). Also, analytics methods might be unreliable in some cases. Reference (Clements & Wallin, 2017) states that These techniques might measure learners' behavior instead of actual learning. Without using theoretical and pedagogical aspects, data analysis methods might fail to determine the reasons for what is happening in the educational system. However, the research focusing on pedagogy and learning analytics is in the beginning steps (Avella et al., 2016), and its combination with big data might add more complexities. Finally, the result section's findings indicate that big data analytics is limited to higher education and few special programs in elementary schools, such as game design and stem education.

4.6 Conclusion

Big data in education has promoted researchers to explore the possibilities of introducing different technologies to enhance students' learning. While the focus remains on prediction and data analysis, less attention has been paid to data management, privacy, and theoretical concepts. At the management and policy level, maintaining privacy and confidentiality along with efficient analytics remains a challenge. Also, the lack of theory-informed analysis can prevent reliable interpretations of the learning process based on analysis results.

Future research needs to explore these challenges and be aware of all required aspects for big data analysis in education, including theory, technology, and management. Each of these three dimensions might have a different viewpoint toward different steps of data analytics in education (i.e., data collection, preprocessing, data analysis, and presentation). Considering these various views, researchers can better understand the field.

4.7 References

Alloghani, M., Al-Jumeily, D., Hussain, A., Aljaaf, A. J., Mustafina, J., & Petrov, E. (2018). Application of machine learning on student data for the appraisal of academic performance. In *2018 11th International Conference on Developments in eSystems Engineering (DeSE)* (pp. 157–162). https://doi.org/10.1109/DeSE.2018.00038

Avella, J., Kanai, T., & Kebritchi, M. (2016). Learning Analytics Methods, Benefits, and Challenges in Higher Education: A Systematic Literature Review. *Online Learning Journal*, *20*(2), 13–29. https://doi.org/10.24059/olj.v20i2.790

Chou, C.-Y., Tseng, S.-F., Chih, W.-C., Chen, Z.-H., Chao, P.-Y., Lai, K., … Lin, Y.-L. (2017). Open student models of core competencies at the curriculum level: using learning analytics for student reflection. *IEEE Transactions on Emerging Topics in Computing*, *5*, 32–44. https://doi.org/10.1109/TETC.2015.2501805

Clements, K., & Wallin, E. (2017). *Innovations to design personalized learning environments for stem education of the future*. https://doi.org/10.21125/edulearn.2017.1823

Daniel, B. K. (2019). Big Data and data science: A critical review of issues for educational research. *British Journal of Educational Technology*, *50*(1), 101–113. https://doi.org/10.1111/bjet.12595

Deveaud, R., SanJuan, E., & Bellot, P. (2014). Accurate and effective Latent Concept Modeling for ad hoc information retrieval. *Document Numerique*, *17*(1), 61–84. https://doi.org/10.3166/dn.17.1.61-84

Doleck, T., Lemay, D. J., Basnet, R. B., & Bazelais, P. (2020). Predictive Analytics in

Education: A Comparison of Deep Learning Frameworks. *Education and Information Technologies*.

Elia, G., Solazzo, G., Lorenzo, G., & Passiante, G. (2018). Assessing learners' satisfaction in collaborative online courses through a big data approach. *Computers in Human Behavior, 92*. https://doi.org/10.1016/j.chb.2018.04.033

Farahmand, A., Dewan, M. A. A., & Lin, F. (2020). Student-Facing Educational Dashboard Design for Online Learners. In *2020 IEEE Intl Conf on Dependable, Autonomic and Secure Computing, Intl Conf on Pervasive Intelligence and Computing, Intl Conf on Cloud and Big Data Computing, Intl Conf on Cyber Science and Technology Congress (DASC/PiCom/CBDCom/CyberSciTech)* (pp. 345–349). https://doi.org/10.1109/DASC-PICom-CBDCom-CyberSciTech49142.2020.00067

Ho, L. C., & Shim, K. (2018). Data mining approach to the identification of at-risk students. In *2018 IEEE International Conference on Big Data (Big Data): Seattle, December 10-13: Proceedings.* (pp. 5333–5335). esearch Collection School Of Computing and Information Systems. https://doi.org/10.1109/BigData.2018.8622495

Howell, J. A., Roberts, L. D., Seaman, K., & Gibson, D. C. (2018). Are We on Our Way to Becoming a " Helicopter University "? Academics' Views on Learning Analytics. *Technology, Knowledge and Learning*, *23*(1), 1–20. https://doi.org/10.1007/s10758-017-9329-9

Khanna, L., Singh, S. N., & Alam, M. (2016). Educational data mining and its role in determining factors affecting students academic performance: A systematic review. In *2016 1st India International Conference on Information Processing (IICIP)* (pp. 1–7). https://doi.org/10.1109/IICIP.2016.7975354

Klašnja-Milićević, A., Ivanović, M., & Budimac, Z. (2017). Data science in education: Big data and learning analytics. *Computer Applications in Engineering Education*, *25*(6), 1066–1078. https://doi.org/10.1002/cae.21844

Larionova, V., Brown, K., & Lally, V. (2019). Integrating lifelong learning within the smart city paradigm. In *13th International Technology, Education and Development Conference* (pp. 5305–5310). https://doi.org/10.21125/inted.2019.1317

Liu, M., Li, C., Pan, Z., & Pan, X. (2019). Mining big data to help make informed decisions for designing effective digital educational games. *Interactive Learning Environments*, *0*(0), 1–21. https://doi.org/10.1080/10494820.2019.1639061

Longabaugh, B. (2012). Visualizing Adjacency Matrices in Python. Retrieved November 14, 2017, from http://sociograph.blogspot.com/2012/11/ visualizing-adjacency-matrices-in-python.html.

Luan, H., Geczy, P., Lai, H., Gobert, J., Yang, S. J. H., Ogata, H., … Tsai, C. C. (2020). Challenges and Future Directions of Big Data and Artificial Intelligence in Education. *Frontiers in Psychology*, *11*(October), 1–11. https://doi.org/10.3389/fpsyg.2020.580820

Moscoso-Zea, O., Andres-Sampedro, & Luján-Mora, S. (2016). Datawarehouse design for educational data mining. In *2016 15th International Conference on Information Technology Based Higher Education and Training (ITHET)* (pp. 1–6). https://doi.org/10.1109/ITHET.2016.7760754

Otoo-Arthur, D., & Van Zyl, T. (2019). A systematic review on big data analytics frameworks for higher education - Tools and algorithms. *ACM International Conference Proceeding Series*, 79–87. https://doi.org/10.1145/3377817.3377836

Quadir, B., Chen, N. S., & Isaias, P. (2020). Analyzing the educational goals, problems and techniques used in educational big data research from 2010 to 2018. *Interactive Learning Environments*, *0*(0), 1–17. https://doi.org/10.1080/10494820.2020.1712427

Riffai, M., Duncan, P., Edgar, D., & Al-Bulushi, A. H. (2016). The potential for big data to enhance the higher education sector in Oman. In *2016 3rd MEC International Conference on Big Data and Smart City (ICBDSC)* (pp. 1–6). https://doi.org/10.1109/ICBDSC.2016.7460346

Santos, K., Menezes, A., Carvalho, A., & Montesco, C. (2019). Supervised Learning in the Context of Educational Data Mining to Avoid University Students Dropout (pp. 207–208). https://doi.org/10.1109/ICALT.2019.00068

Shankar, S. K., Rodríguez-Triana, M. J., Ruiz-Calleja, A., Prieto, L. P., Chejara, P., & Martínez-Monés, A. (2020). Multimodal data value chain (M-DVC): a conceptual tool to support the development of multimodal learning analytics solutions. *IEEE Revista Iberoamericana de Tecnologias Del Aprendizaje*, *15*(2), 113–122. https://doi.org/10.1109/RITA.2020.2987887

Shorfuzzaman, M., Hossain, M. S., Nazir, A., Muhammad, G., & Alamri, A. (2019). Harnessing the power of big data analytics in the cloud to support learning analytics in mobile learning environment. *Computers in Human Behavior*, *92*, 578–588. https://doi.org/https://doi.org/10.1016/j.chb.2018.07.002

Siemens, G., & Baker, R. (2012). Learning analytics and educational data mining: towards communication and collaboration. In *In Proceedings of the 2nd International Conference on Learning Analytics and Knowledge (ACM)* (pp. 252–254). Vancouver, British Columbia, Canada. https://doi.org/https://doi.org/10.1145/2330601.2330661

Sin, K., & Muthu, L. (2015). Application of Big Data in Education Data Mining and Learning Analytics – a Literature Review. *ICTACT Journal on Soft Computing*, *05*(04), 1035–1049. https://doi.org/10.21917/ijsc.2015.0145

Sweeney, M., Lester, J., & Rangwala, H. (2015). Next-term student grade prediction. In *2015 IEEE International Conference on Big Data (Big Data)* (pp. 970–975). https://doi.org/10.1109/BigData.2015.7363847

Thompson, K. (2013). Using micro-patterns of speech to predict the correctness of answers to mathematics problems: an exercise in multimodal learning analytics. In *ICMI 2013 - Proceedings of the 2013 ACM International Conference on Multimodal*

Interaction. https://doi.org/10.1145/2522848.2533792

Wong, G. K. W., & Li, S. Y. K. (2016). Academic Performance Prediction Using Chance Discovery from Online Discussion Forums. In *Proceedings - International Computer Software and Applications Conference* (Vol. 1, pp. 706–711). IEEE. https://doi.org/10.1109/COMPSAC.2016.44

Chapter 5

5 Data-Driven Understanding of Computational Thinking Assessment: A Systematic Literature Review

A movement to include problem-solving and computer science in k-12 education has sparked significant interest in introducing computational thinking (CT). CT education is mainly defined as teaching and learning problem-solving skills. CT is considered a 21-century skill, and like other essential skills aiming to educate students as efficient members of the technology-dependent society, CT learning and assessment are associated with the use of technology-enhanced learning methods and environments. Although most researchers categorize CT skills into three groups, including CT concepts, practices, and perspectives, there is no consensus view regarding CT assessment methods to evaluate these three CT skill categories. Addressing this gap, we explored key topics in the literature of computational thinking assessment (CTA). Using a data-driven approach for topic modeling, we analyzed 395 scientific articles in CTA literature and identified 11 research topics. We implemented Latent Dirichlet Allocation (LDA) topic modeling to identify the latent topic in the CTA literature. Also, we performed a network analysis to explore the key links between CTA's identified topics. Based on the results from topic modeling, we categorized the CTA tools based on their assessment strategy and the types of CT skills they aim to evaluate. Also, this study analyzes the identified assessment methods based on the purpose of assessment and the different types of insights they provide for the evaluation of CT skills. The paper discusses the advantages of new forms of CTA through technology compared to traditional assessment methods and provides recommendations for further studies. The outcomes from this study can be used as a guideline for selecting appropriate CTA tools and methods in different learning settings.

5.1 Introduction

The development of new technologies and the emergence of student-centred learning theories have changed the learning environments and educational purposes in recent years. Nowadays, along with the new opportunities that technology-enhanced learning environments provide for students' learning, students are required to learn new forms of skills named new media skills. New media skills are the kind of skills needed to prepare students as members of a technology-dependent society (Jenkins, 2006). Computational thinking (CT), as an essential 21st-century topic, is considered one of the daily life skills rather than a set of skills used by computer programming specialists (Wing 2006; Labusch, 2018). Based on this belief, computational thinking has become a crucial skill that future generations must develop (De-Marcos et al., 2014).

Since 2006, when Wing used the term computational thinking for the first time, scholars have emphasized the need for teaching CT skills at an early age (Papavlasopoulou et al., 2018). However, even with this burgeoning interest, there is a lack of shared understanding of how CT skills can be developed and assessed. Compared to traditional educational skills, CT skills are mainly associated with cognitive and problem-solving abilities and aim to be thought through technologically enhanced environments. The differences of CT learning with traditional education require new methods to assess students' skill acquisition in CT. This study aims to explore CTA literature to address the following questions: a) What topics have been studied in CTA, and what research themes influence CTA? b) What are the assessment methods and tools in CTA, and how can they be improved using the new learning concepts through new media?

5.2 Literature Review

5.2.1 Computational Thinking

Various studies in the literature provide different definitions for CT. Some studies define CT as a cognitive process, while others highlight it as a problem-solving approach (Zhang and Nouri, 2019). CT literature indicates that the definitions differ based on the goals, skills, and context of implementing CT (Tang et al., 2020). Drawing from programming and computing concepts, many researchers defined CT as the process of programming, designing for usability, improving computational concepts, computational problem-solving, and system thinking. On the other hand, the definitions that emerged from CT's non-programming activities focus on CT's operational and real-life applications. The following two paragraphs provide an overview of the formation of CT definition over time.

CT was not a topic of interest until Wing (2006) introduced it as the approach to "solving problems, designing systems, and understanding human behaviour, by drawing on the concepts fundamental to computer science" (p. 33). Also, she stated that computational thinking is about conceptualization, not programming. Later, Guzdial (2008) mentioned CT as a problem-solving process that focuses on abstraction, evaluation, modelling, and automation. With the rise in the importance of CT, the International Society for Technology in Education (ISTE) and the Computer Science Teacher Association (CSTA) defined CT as a problem-solving process that includes the following as its primary characteristics: formulating problems, logical thinking, representing data through abstractions, simulation, automating solutions through algorithmic thinking, and identifying, evaluating, and implementing possible solutions.

All the above definitions are common in that none of them explicitly mentions programming languages for CT acquisition. However, this is not a universal belief about CT. Brennan & Resnick (2012) stated that programming is essential in CT education. Their proposed theoretical framework presented three dimensions including, computational concepts (programming terms of sequences, loops, events, parallelism, conditionals, operators, and data flow), computational practices (iteration, debugging, and abstraction), and computational perspectives (expressing, questioning, and connecting). Another CT framework classifies CT into four dimensions: data practice, modeling and simulation, problem-solving, and system thinking (Weintrop et al., 2016). Since there is no unified CT definition, its definition changes depending on the context and tool (Kirwan et al., 2018). This study uses the CT dimensions presented by Brennan & Resnick (2012).

5.2.2 Computational thinking assessment

The diversity in CT definition indicates that it is impossible to limit CTA to one of the programming or non-programming constructs. As a result, the same as CT definition, the CTA tools and techniques must differ based on CT's various implementations. Also, the discussions surrounding CT definitions indicate the complex structure of CT (Allsop, 2019). So, it is not practical to restrict CTA to programming constructs as the CT process also involves practices and perspectives. Exploring CTA literature, we can find various assessment techniques and methods, including qualitative, quantitative, and mixed-method approaches (Weese, 2016).

5.3 Method

Given the diversity in CTA, we relied on an unsupervised machine learning approach to develop CTA topics from the literature. Unsupervised machine learning is a technique to discover latent dataset categories (Deveaud et al., 2014). The steps of the conducted systematic literature review are discussed in the following.

5.3.1 Data collection

We obtained peer-reviewed conference and journal publications in CTA from five databases, including ACM, IEEE, Scopus, Web of Science, and ScienceDirect, as shown in Table 2 The data source included titles, abstracts, and keywords of research items in CTA literature. Referring to Wing's (2006) study as the starting point for the CT studies, we retrieved all related publications since 2006. The query used for data collection was {Topic: ("computational thinking" AND (measur* OR assess* OR evaluat* OR "learning analytics" OR "data mining")}. The word "Topic" in the search query refers to the articles' titles, abstracts, and keywords.

Table 2. Overview of Data Collection and Data Selection

Data Source	Number of Search results	Number of Selected research items
ACM	218	112
Web of Science	534	192
IEEE	153	59
Scopus	422	174
ScienceDirect	40	33
Total	1,367	570

5.3.2 Data Selection

Two researchers manually checked the search results regarding their relevance to the CTA field. Also, we excluded the literature review papers as they include a wide range of various concepts. Table 2 shows the number of selected documents from the scientific databases.

5.3.3 Data preprocessing

Preprocessing of data refers to the process of identifying a collection of meaningful data items and word-features. This collection is called core vector space (CVS). Our original collected data included 570 documents with a total of 5,462 word-features. Aiming to find a homogenous CVS, we performed the following preprocessing tasks: duplicate removal, outlier removal, stop word elimination, lowercasing, special character removal, n-gram processing, lemmatization, and normalization based on CT context to standardize the different word forms. Finally, we used the Sklearn python package to identify relevant word-features. During that process, the following groups of words were deleted: words appeared less than two times in the dataset, significantly high-frequency CT-related words, high-frequency words commonly used in scientific contexts, document-related words such as acronyms, and general English words. This process led to the selection of a CSV with 395 research documents and 356 word-features.

5.3.4 Data analysis

We performed Latent Dirichlet Allocation (LDA) from python's Gensim package to find the hidden topics in the CVS. Although LDA is an unsupervised machine learning technique, it must be given the number of topics as a parameter. Four metrics, including Arun2010, CaoJuan2009, Deveaud2014, and Griffiths2004 (Cao et al., 2009; Deveaud et al., 2014), were used to identify the number of topics. This analysis led to the selection of 11 topics as the optimal number of clusters for topic modeling and network analysis.

5.4 Findings

This section presents the results from topic modeling and network analysis.

5.4.1 Computational Thinking Assessment Topics

The following paragraphs of this section present a description of each of the 11 identified topics of CTA. The sample studies mentioned for each topic are among the ten top documents of each topic. In Figure 8, which represents these 11 research topics, a binary adjacency matrix visualizes the topics. The black cells of the matrix show similarity between the two corresponding documents, and the borders represent the topics of documents. Each cluster's size is associated with the number of documents within that cluster, and the density of clusters shows the homogeneity of the associated topics. For interpreting and naming the obtained topics, we considered both the size and homogeneity of the topics.

Topic 1, named "Teacher development", addresses studies related to enhancing and evaluating teaching concepts in CT, including CT curriculum, pedagogy (Kang et al., 2018), and teacher development in both CT knowledge and teaching skills. The methods for the assessment of teachers' knowledge include surveys, self-assessment (Kang et al., 2018), and evaluation of self-efficacy and attitude toward coding and teaching CT (Rich et al., 2020).

Topic 2, named "Problem-Solving Skills", refers to concepts from complex problem-solving skills. Studies in this topic mainly include two types of assessment: First, tools to measure cognitive abilities required for reasoning and problem-solving (Román-González et al., 2017); Second, methods to evaluate the impact of programming on cognitive development (Park et al., 2015). Cognitive development is significant as it can promote students' problem-solving abilities. Problem-solving competencies are among 21st-century skills and refer to cognitive-related skills such as programming and mathematical thinking.

Measuring cognitive skills can reveal students' capabilities for acquiring CT skills. Also, this topic addresses the measurement of intelligence and psychometric (Hubwieser and Mühling, 2015) aspects related to learning CT. The main computational assessment tools in the studies of this topic are statistical methods.

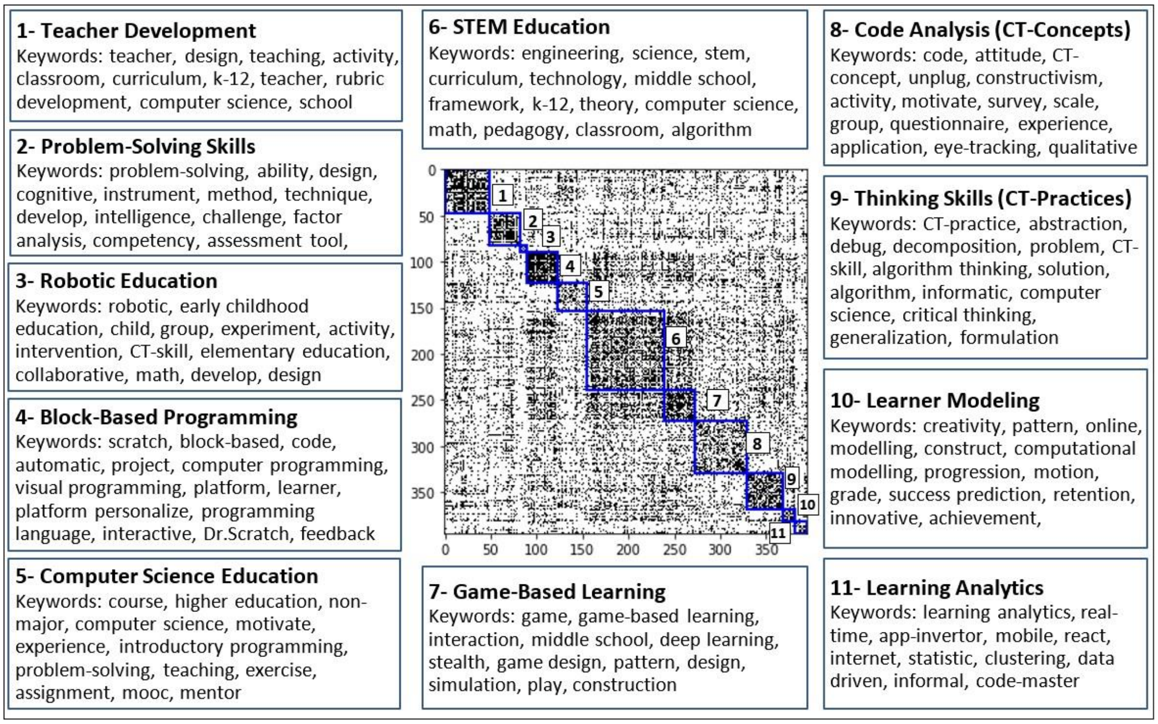

Figure 8. Identified Research Topics for CTA

Topic 3, named "Robotic Education", mainly addresses CT learning for early childhood and elementary level students. This topic includes both unplugged (Miller et al., 2019) and plugged-in (Kong, Chiu, and Lai, 2018) activities in k-12 education. Robot programming can be used in various educational levels, such as maze-solving robot programming for high schoolers (Fronza, Ioini, and Corral, 2017) and tangible robot programming for kindergarteners (Roussou and Rangoussi, 2020). Collaborative learning and teacher intervention are among the main concept related to assessment in the studies of this topic.

Topic 4, named “Block-Based Programming”, addresses CTA in Scratch programming. Scratch is a popular block-based programming software developed to promote CT knowledge in elementary and middle-grade learners (Brennan, Chung, and Hawson, 2011). This topic addresses Dr.Scratch as an automatic web-based tool for assessing Scratch projects and SAT as a modern scratch project analysis tool (Chang et al., 2018). These assessment tools mainly evaluate students’ skills in the CT concepts dimension.

Topic 5, named “Computer Science Education, " refers to assessing problem-solving skills in university-level programming courses. The studies included in this topic use a wide range of qualitative, quantitative, and mixed-method approaches for CT evaluation (Romero et al., 2017; Weese, 2016).

Topic 6 is named “STEM Education” and is related to developing and improving the CT curriculum and pedagogy to integrate CT in STEM education. The CTA methods and techniques in this cluster include rubric-based assessment (Bortz et al., 2019), summative assessment such as national exams (Zur-Bargury et al., 2013), formative assessment (Hadad Roxana and Thomas, 2019), and self-assessment of students. Except for CT concepts and practices, some studies of this topic evaluate the skills in the CT perspective dimension.

Topic 7, named “Game-Based learning”, addresses CT development through playing (Hooshyar et al., 2021) and game construction (Jenson and Droumeva, 2016). This topic includes different assessment methods, such as evaluating learners’ reflection interviews (Litts, Lewis and Mortensen, 2019), analyzing students’ game development artifacts based on programming constructs (Werner, Denner and Campe, 2015), measuring students’ motivation during playing games, and the use of machine learning and deep-learning techniques (Min et al., 2019) to predict students' CT learning.

Topic 8, named "Code Analysis", mainly refers to assessing CT concepts using different code evaluation methods. For example, eye-tracking is a recent technique for analyzing students' coding activities (Papavlasopoulou et al., 2020). This topic also includes evaluating students' attitudes during and after coding activities. Except for computational methods, some studies used qualitative analysis, such as interviews (Benvenuti, Chioccariello and Giammoro, 2018) and pre/post-test analysis of students' coding skills (Arfé et al., 2020).

Topic 9, named "Thinking Skills", mainly refers to evaluating CT practices, such as abstract thinking and decomposition (Djambong Takam and Freiman, 2018; Sondakh, Osman, & Zainudin, 2020).

Topic 10, named "Learner Modeling", refers to modelling and predicting students' CT learning, creativity, innovative thinking, attitude, and success rate using computational methods (Rao et al., 2018).

Topic 11 is named "Learning Analytics" and refers to automatic or real-time methods of evaluating students' CT skills. This topic addresses the use of statistics, data-mining (Souza et al., 2019), machine-learning (Jeon et al., 2018), and learning analytics (Grover et al., 2017).

5.4.2 Network and Factor Analysis.

Figure 9 shows a network of the 11 identified topics. The nodes represent the corresponding topics in Figure 8. Each node is connected to at least three most similar nodes based on topic keywords.

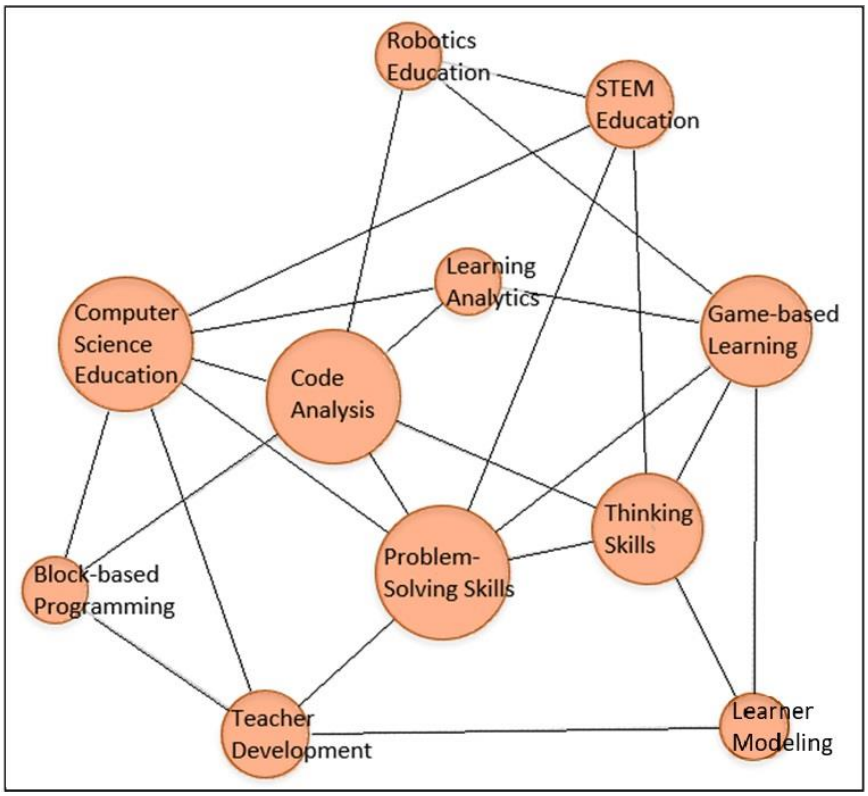

Figure 9. Network of research topics

5.5 Discussion

Addressing the first research question, we identified 11 topics in the result section and presented a network of topics based on common top keywords of topics. In Figure 9 the larger network nodes represent the topics with higher similarity to the other topics. Also, the size of nodes is associated with their related topics' frequency in the CTA literature.

Based on the network analysis results, “Computer Science Education” is one of the main topics in CTA. Different studies utilized assessment methods from computer science, such as “Code Analysis”, to assess CT artifacts. The development of Coding skills in CT aims to enhance students’ “Problem-Solving” and “Thinking Skills” through learning environments suitable for CT education. “Game-based Learning”, “STEM Education”, and “Robotics Education” are three technology-enhanced educational environments for CT education. However, regarding the use of technology and new media, we must be aware that new media does not necessarily mean new learning/assessment (Cope and Kalantzis, 2013). Although digital media through games, coding, and robotics education can provide a flexible and exciting learning environment for CT learners, as long as the computational assessment is only a digitized form of traditional assessment, CTA will not help students perform better through the use of technology. As a result, the studies related to “learning analytics” and “computational modelling” in the CTA field should provide those forms of insights and information that cannot be obtained without computational methods. For reporting assessment results, learning analytics dashboards are another tool that can improve CT assessment by assisting teachers to achieve a better understanding of students’ learning. Finally, the studies related to the “Teacher Development” topic address enhancing teachers’ knowledge of CT, developing skills required for teaching and assessing students’ CT learning, and measuring teachers’ attitudes toward CT. Teacher development is mainly related to educating teachers in coding, block-based programming, and robotics, as these areas are the most common learning environments for formal CT education in schools.

Responding to the second research question, we have categorized the key CTA tools and methods mentioned in the identified CTA topics into 8 categories: diagnostic assessment, formative assessment, summative assessment, self-assessment, peer-assessment, assessment to transfer skill, learning analytics, and mixed-method assessment. These categories of CTA tools and methods are discussed in the following.

5.5.1 Diagnostic Assessment

These types of tests can aptitude test for CT. Their advantage is that they can be used in pre-test conditions. Bloom (1956) says that "it is difficult to classify educational objectives and test items as abilities or skills without full knowledge of students' prior experience." Also, diagnostic tools can activate students' prior knowledge of CT. Shepard (2000) believes that the activation of prior knowledge can be considered as assessment. Grover, Pea, & Cooper (2015) used a pre-test to measure computer programming interest and attitude. This study states that prior knowledge is a strong predictor of CT learning outcomes. Some of the CT diagnostic assessment tools are the Computational Thinking Test (Roman-Gonzalez, Perez-Gonzalez, & Jimenez-Fernandez, 2017; Roman Gonzalez, 2015), the Commutative Assessment Test (D Weintrop et al., 2014), and a test for measuring basic programming skills (Mühling, Ruf, & Hubwieser, 2015).

5.5.2 Formative Assessment

Formative assessment refers to on-going assessment and occurs during the learning process (Shepard, 2000). Formative evaluation is popular in CT education. The use of Dr.Scratch is an example of this formative strategy. To assign CT score to students, Dr.Scratch measures students' Scratch programs in seven concepts: problem decomposition and abstraction, logical thinking, parallelism, synchronization, flow control, user interactivity, and data representation. (Moreno León et al., 2015). The evaluation result from the Dr.Scratch tool can be used as a formative assessment.

Foundations for Advancing Computational Thinking (FACT) is another example, which is a course designed and tested by Grover, Pea, & Cooper (2015). FACT has multiple-choice, low-stakes, and high-frequency quizzes that measure students' understanding of computational concepts and gives hints for further enhancement. Another formative tools, introduced by Basawapatna, Repenning, & Koh (2015), is a cyberlearning system named Real-Time Evaluation and Assessment of Computational Thinking (REACT). This tool provides real-time evaluation corresponding to each student's project. Finally, the Functional Understanding Navigator! or FUN! tool is an automated assessment tool for Scratch projects designed by Brasiel Sarah and Close (2017). From all CT skills, the Fun! tool measures parallelism, logical thinking(e.g., conditional logic, operators, events), synchronization, logical thinking, and pattern generalization (Brasiel et al., 2017).

5.5.3 Summative Assessment

This kind of assessment aims to evaluate learners' content knowledge at the end of a course or each lesson. Summative assessment in CT is not as common as formative assessment. And the limited number of existing studies utilize summative CT assessment to enhance future courses and are not high-stake exams. Some of these summative assessment tools are Fairy assessment to measure algorithmic thinking and effective use of abstraction and modelling (Werner, Denner, Campe, & Kawamoto, 2012), the Quizly tool (Maiorana, Giordano, &Morelli, 2015) for assessing content knowledge, and a rubric based on Bloom's Taxonomy (Sáez-López, 2016) to evaluate students' CT skills by measuring the degree of increase in knowledge for each CT skill. Based on (Bloom 1956), the degree of an increased level of knowledge indicates the increased knowledge in general.

5.5.4 Self-assessment

Involving students in their own assessment gives them ownership over the learning process and improves their cognitive development (Shepard, 2000). The #5c21 model (Romero and Lepage, 2017) is a revised form of three assessment models: CSTA (Computer Science Teachers Association's), Barefoot, and Dr.Scratch, and uses self-assessment of learners CT assessment strategy. Another research (Moreno León et al., 2015) uses Dr.Scratch as a self-assessment tool that acts as a tutorial about how learners can improve their codes.

5.5.5 Peer Assessment

The same as self-assessment, peer assessment is used in CTA to give students the agency of their learning process and motivate them. Students can learn from each other during peer assessment, question themselves and their peers, discuss their code, and find a solution. Both self-assessment and peer-assessment activities let teachers ignore students' mistakes and involve students in their learning. Teachers might provide comments to make students question themselves and find solutions. Portelance et al. (2015) analyzed recorded videos from the peers' artifact-based interviews and measured CT skills, including sequencing, parallel programming, reusing, expressing, reusing, connecting, and expressing. Also, the FACT assessment tool by Grover et al. (2015) includes social and participatory aspects of learning environments using artifact-based interviews. Finally, using the Scratch website, students can demonstrate their games to the entire class, provide documentation, write reflections, and provide feedback for their peer's Scratch games.

5.5.6 Assessment to Transfer Skills

When students practice with a variety of applications in the process of learning, knowledge is more likely to transfer (Shepard, 2000). In CT learning environments, students can test their problem-solving ideas for any given problem, learn from their peers, discuss with them, and learn new solutions.

Hoover et al. (2016) Analyzed students’ Scratch games with qualitative analysis of design choices. This method analyzes the relationship between students’ final choices to design their games and their CT scores from Dr.Scratch. Their approach aims to improve the effectiveness of Dr.Scratch’s feedbacks. Rowe, Asbell-Clarke, Cunningham, & Gasca (2017) utilized a human labelling system for assessing four CT skills: problem decomposition, algorithmic thinking, pattern recognition, and abstraction. Romero et al. (2017) designed just in time teacher-based evaluations as a human-centred approach to improve students’ learning process. Grover, Bienkowski, Niekrasz, & Hauswirth (2016) used a qualitative strategy to find the patterns of students’ behaviours in CT games. In the FACT framework (Grover et al., 2015), a test assessed students’ ability to transfer their programs in the block-based Scratch environment to Pascal/Java-like code. Finally, Grover et al. (2015) assessed affective aspects like students’ improvement in their understanding of computing through free-response questions.

5.5.7 Learning Analytics for Assessment

Utilizing computer-based techniques to analyze game logs or students’ behaviour has been studied by different researchers in the CT assessment literature. Srinivas and Roy (2018) used logs from the process of designing Scratch games by students to measure CT concepts and practices based on dimensions defined in Brennan & Resnick's framework (2012). Montaño Juan and Mondragón (2019) used data analytics to analyze students’ performance in gamified CT environments. Data mining approaches are among the best methods to measure CT concepts and practices. However, they are not suitable for measuring creativity, which is a skill in the highest cognitive levels.

5.5.8 Mixed-Method Assessment

Since all CT skills cannot be measured by one assessment method, many studies have introduced mixed-method techniques to thoroughly analyze CT skills. Grover, Bienkowski, Niekrasz, & Hauswirth (2016) combined qualitative, quantitative, hybrid hypothesis and discovery-driven strategy to find the patterns of behaviours in logs from *Blocky* games and measure computational thinking practices. Also, the #5c21 model is a combination of three assessment methods and aims to measure creative programming (Romero et al., 2017) by combining automated and qualitative assessment approaches.

5.6 Conclusion

This study identified eleven topics in CTA literature from 2006 to 2021 and used a network of topics to explore the topic connections. Also, assessment tools and methods for CT were discussed and categorized into eight groups. The CTA literature shows a growing interest in automated and computer-based assessment tools. This tendency can lead to effective understanding of students' learning and improve CT education in future. However, we believe the following essential challenges have not been addressed in the literature.

First, based on the literature, we can imply that CT education uses different technology-enhanced learning environments to improve students' problem-solving skills. However, the use of technology as new media or assessment tool does not guarantee new forms of learning. In some computational assessment practices, the rush to adapt to technology-enhanced learning can develop old ways of assessment using new technologies. For CTA to assess required 21-century skills, the assessment methods should focus on student-centred learning theories and provide insights that are not accessible using traditional assessment.

Second, although automated assessment can lead to new forms of assessment and provide new understandings of students' learning, automatic assessment methods primarily focus on the level of code complexity, not the meaning (Hoover et al., 2016). As a result, the automated methods measure technical mastery, not creativity, which is a skill in the highest cognitive levels. Based on Dewey's "theory of creativity," creativity should be measured by the usefulness of a solution, its value, and originality (Mihai, 2016). In recent years, through qualitative methods and learner modelling, the attempts to measure higher cognitive levels of CT skills are rising, and authors are becoming more interested in adopting multiple evaluation approaches to address more CT skills using automatic assessment (Allsop, 2019). For example, based on the topic modelling results, we can imply that even though there are fewer studies for assessing CT perspectives dimension, most of these studies have been conducted in recent years, and this research area is growing.

The advancement in the automatic assessment of education can significantly improve CT learning. The following are among the possible future directions in automatic assessment of CT: student modelling based on learner behaviour, using data analytics techniques and dashboards to create user-friendly reports, multimodal assessment, personalization of learning process and assessments based on students' interest, behaviour, and academic differences. Also, in the future, extensive use of advanced computational methods such as image processing, face and gesture detection, and wearable sensors can improve CTA and decrease the need for human-based qualitative assessment methods for evaluating CT at higher cognitive levels.

5.7 References

Allsop, Y. (2019) 'Assessing computational thinking process using a multiple evaluation approach', *International Journal of Child-Computer Interaction. Vol. 19*, pp. 30–55. doi: 10.1016/j.ijcci.2018.10.004.

Arfé, B., Vardanega, T. and Ronconi, L. (2020) 'The effects of coding on children's planning and inhibition skills', *Computers & Education, 148*, p. 103807. doi: https://doi.org/10.1016/j.compedu.2020.103807.

Benvenuti, M., Chioccariello, A. and Giammoro, G. (2018) 'Programming to learn in Italian primary school', in Cutts, Q and Brinda, T (ed*.) Proceedings of the 14th Workshop in Primary and Secondary Computing Education (WIPSCE)*. doi: 10.1145/3361721.3361732.

Bortz, W. W. et al. (2019) 'Missing in Measurement: Why Identifying Learning in Integrated Domains Is So Hard', *Journal of Science Education and Technology*. doi: 10.1007/s10956-019-09805-8.

Brasiel Sarahand Close, K. and J. S. and L. K. and J. P. and M. T. (2017) 'Measuring Computational Thinking Development with the FUN! Tool', in Rich Peter J.and Hodges, C. B. (ed.) *Emerging Research, Practice, and Policy on Computational Thinking. Cham: Springer International Publishing*, pp. 327–347. doi: 10.1007/978-3-319-52691-1_20.

Brennan, K., Chung, M. and Hawson, J. (2011) Scratch Curriculum Guide Draft, *Harvard Graduate School of Education*. Available at: http://scratched.gse.harvard.edu/resources/scratch-curriculum-guide-draft (Accessed: 3 July 2021).

Brennan, K. and Resnick, M. (2012) 'New frameworks for studying and assessing the development of computational thinking', in *American Educational Research Association*. Vancouver, Canada, pp. 135–160. doi: 10.1007/978-3-319-64051-8_9.

Cao, J. et al. (2009) 'A density-based method for adaptive LDA model selection', *Neurocomputing, Vol. 72, No. 7*, pp. 1775–1781. doi: https://doi.org/10.1016/j.neucom.2008.06.011.

Chang, Z. et al. (2018) 'Scratch Analysis Tool(SAT): A Modern Scratch Project Analysis Tool based on ANTLR to Assess Computational Thinking Skills', in 2018 14th *International Wireless Communications Mobile Computing Conference (IWCMC)*, pp. 950–955.

Cope, B. and Kalantzis, M. (2013) ‘New Media, New Learning and New Assessments’, *E-Learning and Digital Media. SAGE Publications, Vol. 10, No. 4,* pp. 328–331. doi: 10.2304/elea.2013.10.4.328.

De-Marcos, L. et al. (2014) ‘An empirical study comparing gamification and social networking on e-learning’, *Computers and Education.*

Deveaud, R., SanJuan, E. and Bellot, P. (2014) ‘Accurate and effective Latent Concept Modeling for ad hoc information retrieval’, *Document Numerique, Vol. 17, No. 1,* pp. 61–84. doi: 10.3166/dn.17.1.61-84.

Djambong Takamand Freiman, V. and G. S. and P. M. and C. M. (2018) ‘Measurement of Computational Thinking in K-12 Education: The Need for Innovative Practices’, in *Sampson Demetriosand Ifenthaler, D. and S. J. M. and I. P. (ed.) Digital Technologies: Sustainable Innovations for Improving Teaching and Learning. Cham: Springer International Publishing,* pp. 193–222. doi: 10.1007/978-3-319-73417-0_12.

Fronza, I., Ioini, N. El and Corral, L. (2017) ‘Teaching Computational Thinking Using Agile Software Engineering Methods: A Framework for Middle Schools’, *ACM Trans. Comput. Educ.* New York, NY, USA: ACM, Vol. 17, No. 4, pp. 19:1–19:28. doi: 10.1145/3055258.

Grover, S. et al. (2017) ‘A Framework for Using Hypothesis-Driven Approaches to Support Data-Driven Learning Analytics in Measuring Computational Thinking in Block-Based Programming Environments’, *ACM Trans. Comput. Educ.* New York, NY, USA: ACM, Vol. 17, No. 3, pp. 14:1–14:25.

Grover, S., Pea, R. and Cooper, S. (2015) ‘Designing for deeper learning in a blended computer science course for middle school students’, *Computer Science Education*. Routledge, Vol. 25, No. 2, pp. 199–237. doi: 10.1080/08993408.2015.1033142.

Guzdial, M. (2008) ‘Education paving the way for computational thinking’, *Communications of the ACM,* Vol. 51, No. 8, pp. 25–27. doi: https://doi.org/10.1145/1378704.1378713.

Hadad Roxanaand Thomas, K. and K. M. and Y. Y. (2019) ‘Practicing Formative Assessment for Computational Thinking in Making Environments’, *Journal of Science Education and Technology*. doi: 10.1007/s10956-019-09796-6.

Hooshyar, D. et al. (2021) ‘An adaptive educational computer game: Effects on students’ knowledge and learning attitude in computational thinking’, *Computers in Human Behavior, Vol. 114,* p. 106575. doi: https://doi.org/10.1016/j.chb.2020.106575.

Hubwieser, P. and Mühling, A. (2015) ‘Investigating the Psychometric Structure of Bebras Contest: Towards Mesuring Computational Thinking Skills’, in 2015 *International Conference on Learning and Teaching in Computing and Engineering,* pp. 62–69.

Jenkins, H. (2006) ‘Confronting the Challenges of Participatory Culture: Media Education for the 21st Century. An Occasional Paper on Digital Media and

Learning.', *John D. and Catherine T. MacArthur Foundation, Vol. 2, No. 2,* pp. 97–113.

Jenson, J. and Droumeva, M. (2016) 'Exploring Media Literacy and Computational Thinking: A Game Maker Curriculum Study', *Electronic Journal of e-Learning, Vol. 14, No. 2,* pp. 111–121.

Jeon, H., Oh, H. and Lee, J. (2018) 'Machine Learning based Fast Reading Algorithm for Future ICT based Education', in 2018 *International Conference on Information and Communication technology Convergence*. New York, NY, USA, pp. 771–775.

Kang, E. J. S., Donovan, C. and McCarthy, M. J. (2018) 'Exploring Elementary Teachers' Pedagogical Content Knowledge and Confidence in Implementing the NGSS Science and Engineering Practices', *Journal of Science Teacher Education, Vol. 29, No. 1,* pp. 9–29. doi: 10.1080/1046560X.2017.1415616.

Kirwan, C., Costello, E. and Donlon, E. (2018) 'Computational thinking and online learning: A systematic literature review', in *Proceedings of the European Conference on e-Learning, ECEL,* pp. 650–657.

Kong, S.-C., Chiu, M. M. and Lai, M. (2018) 'A study of primary school students' interest, collaboration attitude, and programming empowerment in computational thinking education', *Computers & Education. Pergamon, Vol. 127,* pp. 178–189. doi: 10.1016/J.COMPEDU.2018.08.026.

Labusch, A. (2018) 'Fostering Computational Thinking through Problem-Solving at School', in *Proceedings of the 2018 ACM Conference on International Computing Education Research*. New York, NY, USA: Association for Computing Machinery (ICER '18), pp. 276–277.

Litts, B. K., Lewis, W. E. and Mortensen, C. K. (2019) 'Engaging youth in computational thinking practices through designing place-based mobile games about local issues', *Interactive Learning Environments*. doi: 10.1080/10494820.2019.1674883.

Miller, B. et al. (2019) 'Unplugged Robotics to Increase K-12 Students' Engineering Interest and Attitudes', in Proceedings - *Frontiers in Education Conference, FIE*. Institute of Electrical and Electronics Engineers Inc. doi: 10.1109/FIE.2018.8658959.

Min, W. et al. (2019) 'DeepStealth: Game-Based Learning Stealth Assessment with Deep Neural Networks', *IEEE Transactions on Learning Technologies*, p. 1. doi: 10.1109/TLT.2019.2922356.

Papavlasopoulou, S., Giannakos, M. N. and Jaccheri, L. (2018) 'Discovering children's competencies in coding through the analysis of Scratch projects', in 2018 IEEE *Global Engineering Education Conference*, pp. 1127–1133. doi: 10.1109/EDUCON.2018.8363356.

Papavlasopoulou, S., Sharma, K. and Giannakos, M. N. (2020) 'Coding activities for children: Coupling eye-tracking with qualitative data to investigate gender differences', *Computers in Human Behavior, 105,* p. 105939. doi: https://doi.org/10.1016/j.chb.2019.03.003.

Park, S.-Y., Song, K.-S. and Kim, S.-H. (2015) 'Cognitive load changes in pre-service teachers with Computational Thinking education', *International Journal of Software Engineering and its Applications. Science and Engineering Research Support Society, Vol. 9, No. 10,* pp. 169–178. doi: 10.14257/ijseia.2015.9.10.17.

Rao, R. J. et al. (2018) 'Assessing Learning Behavior and Cognitive Bias from Web Logs', *in 2018 IEEE Frontiers in Education Conference (FIE), Vol. 1,* pp. 1-5.

Rich, P. J., Larsen, R. A. and Mason, S. L. (2020) 'Measuring teacher beliefs about coding and computational thinking', *Journal of Research on Technology in Education.* Taylor and Francis Inc. doi: 10.1080/15391523.2020.1771232.

Román-González, M., Pérez-González, J.-C. and Jiménez-Fernández, C. (2017) 'Which cognitive abilities underlie computational thinking? Criterion validity of the Computational Thinking Test', *Computers in Human Behavior. Pergamon, 72,* pp. 678–691. doi: 10.1016/J.CHB.2016.08.047.

Romero, M., Lepage, A. and Lille, B. (2017) 'Computational thinking development through creative programming in higher education', *International Journal of Educational Technology in Higher Education, Vol. 14, No. 42,* p. 15. doi: 10.1186/s41239-017-0080-z.

Roussou, E. and Rangoussi, M. (2020) 'On the use of robotics for the development of computational thinking in kindergarten: Educational intervention and evaluation', Advances in Intelligent Systems and Computing. Edited by K. G. B. R. O. D. Merdan M. Lepuschitz W. Springer Verlag, 1023, pp. 31–44. doi: 10.1007/978-3-030-26945-6_3.

Shepard, L. A. (2000) 'The Role of Assessment in a Learning Culture', Educational Researcher, Vol. 29, No. 7, pp. 4–14. doi: 10.3102/0013189X029007004.

Sondakh, D. E., Osman, K. and Zainudin, S. (2020) 'A proposal for holistic assessment of computational thinking for undergraduate: Content validity', *European Journal of Educational Research. Eurasian Society of Educational Research, Vol. 9, No. 1,* pp. 33–50.

Souza, A. A. de et al. (2019) 'Data Mining Framework to Analyze the Evolution of Computational Thinking Skills in Game Building Workshops', *IEEE Access, 7,* pp. 82848–82866. doi: 10.1109/ACCESS.2019.2924343.

Tang, X. et al. (2020) 'Assessing computational thinking: A systematic review of empirical studies', *Computers and Education. Elsevier Ltd,* 148(January), p. 103798. doi: 10.1016/j.compedu.2019.103798.

Weese, J. L. (2016) 'Mixed Methods for the Assessment and Incorporation of Computational Thinking in K-12 and Higher Education', *in Proceedings of the 2016 ACM Conference on International Computing Education Research*. New York, NY, USA: ACM (ICER '16), pp. 279–280. doi: 10.1145/2960310.2960347.

Weintrop, D. et al. (2016) ‘Defining Computational Thinking for Mathematics and Science Classrooms’, *Journal of Science Education and Technology, Vol. 25, No. 1,* pp. 127–147.

Werner, L., Denner, J. and Campe, S. (2015) ‘Children Programming Games: A Strategy for Measuring Computational Learning’, *ACM Transactions on Computing Education, Vol. 14, No. 4*. doi: 10.1145/2677091.

Wing, J. M. (2006) ‘Computational Thinking’, *Communications of the ACM, Vol. 49, No. 3,* pp. 33–35.

Zhang, L. and Nouri, J. (2019) ‘A systematic review of learning computational thinking through Scratch in K-9’, *Computers & Education. Elsevier, 141, Vol. 141*, p. 103607. doi: 10.1016/j.compedu.2019.103607.

Zur-Bargury, I., Pârv, B. and Lanzberg, D. (2013) ‘A Nationwide Exam as a Tool for Improving a New Curriculum’, *in Proceedings of the 18th ACM Conference on Innovation and Technology in Computer Science Education*. New York, NY, USA: Association for Computing Machinery (ITiCSE ’13), pp. 267–272. doi: 10.1145/2462476.2462479.

Chapter 6

6 Conclusion

In this chapter, I will review the thesis questions presented in the introduction section and proceed to synthesize each study in terms of how they are associated with the thesis questions. Finally, thesis contributions and future research suggestions will be presented based on the findings for each of the studies.

6.1 Review of the Research Questions

The main purpose of this thesis has been to explore the existing learning analytics methods and their possible applications in enhancing learning processes. To fulfill that purpose, we researched existing methods in learning analytics. Also, we studied existing methods in the CTA literature and explored how learning analytics methods can be used in CT to enhance learning processes. Each of the two studies answered some subsequent research questions related to the literature of LA and CTA. In the following, the research questions are mentioned once again:

6.2 Summarizing the chapters

The following two sections summarize chapter four and chapter five of the thesis.

6.2.1 Chapter four: A literature review of Learning Analytics

This thesis is mainly about learning analytics and aims to study their applications in different aspects of educational environments. To pursue this goal, we conducted a systematic data-driven literature review of learning analytics to understand the methods and main. The terminology used for automatic data analysis in education differs in the literature based on the scope and target audiences and includes academic analysis, educational data mining, and learning analytics. We considered all of them in our systematic literature review and restricted our study to the big data analytics scope to ensure that the retrieved articles from the literature are relevant to the concepts in multimodal assessment of learning. A total of 979 research items were retrieved from the literature related to automatic assessment topic in education. After eliminating the duplicate documents, documents indexed in more than one database, and excluding less-relevant documents, a total of 490 documents remained.

Using LDA topic modelling as an unsupervised machine learning method, we identified six research topics: administrative concepts, predictive analytics, learning analytics dashboards, e-learning platforms, learning and teaching, and cloud-based learning. While the administrative concepts topic emphasizes the importance of organizational and administrative level analytics of educational environments, learning analytics dashboards mostly focuses on the calss level analytics and dashboards that can assist teachers to understand students' learning better. Also, while some topics, including eLearning platforms and cloud-based learning, are related to the technological aspects of using learning analytics, predictive analytics topic studies the impact of prediction in preparing resources based upon that prediction learning. Finally, learning and teaching topic emphasizes the importance of including educational theories in the process of analyzing educational data. These six main topics also included 19 subtopics.

Synthesizing the six identified topics and their 19 subtopics, we finally categorized them into three main concepts: theory, technology, and management, based on their related area and audiences. Based on the current literature on data analytics in education. Data analysis is being studied to improve students' learning experiences in classrooms and to assist teachers in better understanding students' needs, but data analysis can also make significant impacts in other scopes such as schools or institutional levels. Finally, we explored the connections between the six identified topics using network analysis of topics.

Regarding the thesis research questions, the RQ1.1 was answered in the literature review part of the thesis in section 2.3 (Learning Analytics for Learning Assessment) using the qualitative analysis of selective research items from the quantitate analysis dataset. To avoid duplication, we did not include that part in the first article. Regarding the RQ1.2 question, the topic modelling and network analysis approach allowed us to understand the general trends and topic interconnections. RQ1.3 question was answered by discussing the main applications of data analytics in education in the six main identified topics. The 19 subtopics also allowed us to synthesize each of the six topics and explore the data analysis methods and technological aspects utilized the most in each application.

6.2.2 Chapter five: Computational Thinking Literature Review

Chapter five studies assessment in CT literature and includes both human-based and automatic assessment practices. Along with CT's different definitions and educational goals, CTA methods and tools also differ in various contexts and educational environments. Using a systematic literature review, chapter five explores the existing forms and assessment methods in CT education literature.

Chapter five conducted a systematic literature review and retrieved 570 research documents from CT-related databases. A total of 395 documents remained after eliminating duplicate items and excluding the non-relevant items by manual checks. Pre-processing of the 395 items and selecting relevant word-features resulted in a database with around 400 CT-related keywords. We implemented LDA topic modelling and identified 11 topics, including robotics education, stem education, learning analytics, game-based learning, thinking skills, learner modelling, problem-solving skills, code analysis, teacher development, block-based programming, computer science education. Each of these 11 topics is related to one of the important aspects in CTA, including CT skills, CTA in different environments, and CTA tools. Following topic modelling, the analysis of topic connection, based on common words between topics, provided a better understanding of the field. Identifying problem-solving, code analysis, and computer science education as the most connected topics of the network of the eleven identified CTA topics indicates that problem-solving is among the top skills required in CT education; And researchers are utilizing concepts from computer programming and coding for the assessment of CT.

Regarding the research questions, the RQ2.1 thesis question was answered by identifying the topics in the CTA literature. Scholars have defined and categorized CT skills in different ways; however, not all of those skills are considered equally important in practice and CTA research. Aiming to explore the key CT skills and their corresponding assessment tools, we synthesized the identified eleven CTA topics and answered the RQ2.2 research question. Learning analytics and other automatic assessment tools were discussed in one of the eleven identified topics based on our topic modelling approach. We also used qualitative analysis of selected studies to better understand CT's automatic forms of assessment. Finally, we discussed the automatic assessment tool and the challenges of using them in the CT context to answer the RQ2.3 question.

6.3 Research contribution and significance

As each of the two chapters in this integrated article thesis is a standalone piece, contributions for the studies were mentioned in the corresponding chapters. This thesis mainly aimed to study the different forms of evaluating students' learning and the related challenges. Assessment is the core of learning; however, the literature indicates that there is not enough research to address all aspects and challenges of evaluating students' learning. The first articles of the thesis provides a three-dimensional model to categorize learning assessment challenges based on the three main and interconnected areas in learning assessment. Also, modern educational environments and the significance of learning new media skills require new assessment forms., we explored the different methods and applications of them in the assessment of learning

This thesis studies learning analytics methods and explores the key factors that impact the enhancement of learning analytics. Also, focusing on the automatic form of assessment, this thesis studies both traditional and automatic assessment methods in CT education as an example of an educational field aiming to improve students' new media skills such as problem-solving. The findings from this thesis contribute to the assessment of learning, automatic forms of assessment, and the assessment of new media skills in the education field. Finally, the data-driven systematic literature review approach utilized in this thesis is a novel way of approaching literature review studies in education. This quantitative analysis methods can be used in other educational fields and studies and the codes are available online to be used by other researchers.

6.4 Future work and limitations

Suggestions for future research specific to each study have been mentioned in the corresponding chapters; Therefore, I will not repeat them here. However, I would like to add possible future directions for the other relevant fields when considering the thesis as a whole.

First, even though CT education is a recent field of education and relates to 21-century skills, it has common topics with other fields of education, such as mathematics, computer science, and robotics education. Therefore, various assessment scenarios and study outcomes from similar fields can be used in CT education. Future works may focus on understanding assessment methods, tools, and scenarios from other fields and applying them to CT education based on CT requirements.

Second, future studies in learning analytics except the technological aspects should also focus on the theoretical educational requirements, limitations in learning environments, students' differences, managemental challenges, and ethical issues. Neglecting the non-technological aspects of applying automatic assessment tools in real learning settings can lead to unpractical tools that are only suitable for ideal conditions.

The limitations from this thesis may also be addressed in the future studies to achieve a better outcmes. First, this study only analyzed academic publications in the two area of CT and learning analytics. Future studies may also analyze government or school documents or explore academic publications in other areas related to new media skills. Second limitation of the thesis was that we utilized our quantitative literature review method on the limited sections of research items, including title, keyword, abstract, and metadata. The future studies may use other existing quantitative text analysis techniques such as text summarization to analyze entire documents or reference analysis to analyze the connections between research items and authors. Finally, quantitative analysis of text data can be used for the analysis of a higher number of text documents, but it cannot be considered as a detailed analysis of those research items. As mentioned in the methodology section, this study uses qualitative analysis to answer some of the research questions.

However, the use of qualitative analysis is limited due to scope of the thesis as a master thesis and lack of enough individual for coding and analyzing the text using qualitative methods. Other researchers may use qualitative analyses in larger scales to support their quantitative findings, or use qualitative findings as a guide for designing steps in their quantitative methodology and interpreting the findings from their quantitative analyses.

References

Adeniji, B. (2019). *A Bibliometric Study on Learning Analytics*. Long Island University. Retrieved from https://digitalcommons.liu.edu/post_fultext_dis

Allsop, Y. (2019). Assessing computational thinking process using a multiple evaluation approach. *International Journal of Child-Computer Interaction*, *19,* 30–55. https://doi.org/10.1016/j.ijcci.2018.10.004

Ananiadou, S., Procter, R., & Thomas, J. (2009). Supporting Systematic Reviews Using Text Mining. *Social Science Computer Review*, *27*(4), 509–523. https://doi.org/10.1177/0894439309332293

Arun, R., Suresh, V., Veni Madhavan, C. E., & Narasimha Murthy, M. N. (2010). On Finding the Natural Number of Topics with Latent Dirichlet Allocation: Some Observations BT - Advances in Knowledge Discovery and Data Mining. In M. J. Zaki, J. X. Yu, B. Ravindran, & V. Pudi (Eds.) (pp. 391–402). Berlin, Heidelberg: Springer Berlin Heidelberg.

Aung, K. Z. (2017). Sentiment Analysis of Students ’ Comment Using Lexicon Based Approach. *2017 IEEE/ACIS 16th International Conference on Computer and Information Science (ICIS)*, 149–154. https://doi.org/10.1109/ICIS.2017.7959985

Avella, J., Kanai, T., & Kebritchi, M. (2016). Learning Analytics Methods, Benefits, and Challenges in Higher Education: A Systematic Literature Review. *Online Learning Journal*, *20*(2), 13–29. https://doi.org/10.24059/olj.v20i2.790

Banihashem, S. K., Aliabadi, K., Pourroostaei Ardakani, S., Delaver, A., & Nili Ahmadabadi, M. (2018). Learning Analytics: A Systematic Literature Review. *Interdisciplinary Journal of Virtual Learning in Medical Sciences*, *9*(2). https://doi.org/10.5812/ijvlms.63024

Basawapatna, A. R., Repenning, A., & Koh, K. H. (2015). Closing The Cyberlearning Loop: Enabling Teachers To Formatively Assess Student Programming Projects. In *Proceedings of the 46th ACM Technical Symposium on Computer Science Education* (pp. 12–17). New York, NY, USA: ACM. https://doi.org/10.1145/2676723.2677269

Basogain, X., Olabe, M. Á., Olabe, J. C., & Rico, M. J. (2018). Computational Thinking in pre-university Blended Learning classrooms. *Computers in Human Behavior*, *80*, 412–419. https://doi.org/10.1016/J.CHB.2017.04.058

Bayne, S. (2015). What’s the matter with ‘technology-enhanced learning’? *Learning, Media and Technology*, *40*(1), 5–20. https://doi.org/10.1080/17439884.2014.915851

Blikstein, P., & Worsley, M. (2016). Multimodal Learning Analytics and Education Data Mining : Using Computational Technologies to Measure Complex Learning Tasks. *Journal of Learning Analytics*, *3*(2), 220–238. Retrieved from http://dx.doi.org/10.18608/jla.2016.32.11

Blikstein, P., Worsley, M., Piech, C., Sahami, M., Cooper, S., & Koller, D. (2014). Programming Pluralism: Using Learning Analytics to Detect Patterns in the

Learning of Computer Programming. *Journal of the Learning Sciences*, *23*(4), 561–599. https://doi.org/10.1080/10508406.2014.954750

Blikstein, P., Worsley, M., Piech, C., Sahami, M., Koller, D., Blikstein, P., … Koller, D. (2014). Programming Pluralism : Using Learning Analytics to Detect Patterns in the Learning of Computer Programming Programming Pluralism : Using Learning Analytics to Detect Patterns in the Learning of Computer Programming. *The Journal of the Learning Sciences*, *23*(4), 561–599. https://doi.org/10.1080/10508406.2014.954750

Brasiel Sarahand Close, K. and J. S. and L. K. and J. P. and M. T. (2017). Measuring Computational Thinking Development with the FUN! Tool. In C. B. Rich Peter J.and Hodges (Ed.), *Emerging Research, Practice, and Policy on Computational Thinking* (pp. 327–347). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-319-52691-1_20

Brennan, K., & Resnick, M. (2012). New frameworks for studying and assessing the development of computational thinking. In *American Educational Research Association* (pp. 135–160). Vancouver, Canada. https://doi.org/10.1007/978-3-319-64051-8_9

Brinkhuis, M. J. S., Savi, A. O., Hofman, A. D., Coomans, F., van der Maas, H. L. J., & Maris, G. (2018). Learning as It Happens: A Decade of Analyzing and Shaping a Large-Scale Online Learning System. *Journal of Learning Analytics*.

Cantabella, M., Martínez-España, R., Ayuso, B., Yáñez, J. A., & Muñoz, A. (2019). Analysis of student behavior in learning management systems through a Big Data framework. *Future Generation Computer Systems*, *90*, 262–272. https://doi.org/https://doi.org/10.1016/j.future.2018.08.003

Cao, J., Xia, T., Li, J., Zhang, Y., & Tang, S. (2009). A density-based method for adaptive LDA model selection. *Neurocomputing*, *72*(7), 1775–1781. https://doi.org/https://doi.org/10.1016/j.neucom.2008.06.011

Chatti, M., Dyckhoff, A., Schroeder, U., & Thüs, H. (2012). A Reference Model for Learning Analytics. *International Journal of Technology Enhanced Learning*, *4*(5), 318–331. Retrieved from https://doi.org/DOI: 10.1504/IJTEL.2012.051815

Cukurova, M., Avramides, K., Spikol, D., Luckin, R., & Mavrikis, M. (2016). An Analysis Framework for Collaborative Problem Solving in Practice-Based Learning Activities: A Mixed-Method Approach. In *Proceedings of the Sixth International Conference on Learning Analytics & Knowledge* (pp. 84–88). New York, NY, USA: Association for Computing Machinery. https://doi.org/10.1145/2883851.2883900

Daniel, B. K. (2019). Big Data and data science: A critical review of issues for educational research. *British Journal of Educational Technology*, *50*(1), 101–113. https://doi.org/10.1111/bjet.12595

Dawson, S., & Siemens, G. (2014). Analytics to Literacies: The Development of a Learning Analytics Framework for Multiliteracies Assessment. *International Review of Research in Open and Distance Learning*, *15*(4), 284–305. https://doi.org/10.19173/irrodl.v15i4.1878

Derick, L., Munoz-merino, P. J., & Kloos, C. D. (2017). Evaluating emotion visualizations using AffectVis , an affect-aware dashboard for students, *10*(2), 107–125. https://doi.org/10.1108/JRIT-05-2017-0011

Deveaud, R., SanJuan, E., & Bellot, P. (2014). Accurate and effective Latent Concept Modeling for ad hoc information retrieval. *Document Numerique*, *17*(1), 61–84. https://doi.org/10.3166/dn.17.1.61-84

Doleck, T., Lemay, D. J., Basnet, R. B., & Bazelais, P. (2020). Predictive Analytics in Education: A Comparison of Deep Learning Frameworks. *Education and Information Technologies*.

Feng, L., Chiam, Y. K., & Lo, S. K. (2017). Text-Mining Techniques and Tools for Systematic Literature Reviews: A Systematic Literature Review. In *24th Asia-Pacific Software Engineering Conference (APSEC)* (pp. 41–50). https://doi.org/10.1109/APSEC.2017.10

Ferrell, G. (2012). *A view of the Assessment and Feedback Landscape: baseline analysis of policy and practice from the JISC Assessment & Feedback programme*.

Gomes, J. S., Yassine, M., Worsley, M., & Blikstein, P. (2013). Analysing Engineering Expertise of High School Students Using Eye Tracking and Multimodal Learning Analytics. In *Proceedings of the 6th International Conference on Educational Data Mining* (pp. 375–377).

Gough, D. (2015). Qualitative and mixed methods in systematic reviews. *Systematic Reviews*, 1–3. https://doi.org/10.1186/s13643-015-0151-y

Greller, W., & Drachsler, H. (2012). Translating learning into numbers: a generic framework for learning analytics. *Educational Technology and Society*, *12*(42), 42–57.

Griffiths, T. L., & Steyvers, M. (2004). Finding scientific topics. *Proceedings of the National Academy of Sciences of the United States of America*, *101*(SUPPL. 1), 5228–5235. https://doi.org/10.1073/pnas.0307752101

Grover, S. (2017). Assessing Algorithmic and Computational Thinking in K-12: Lessons from a Middle School Classroom. In C. B. Rich Peter J.and Hodges (Ed.), *Emerging Research, Practice, and Policy on Computational Thinking* (pp. 269–288). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-319-52691-1_17

Grover, S., Bienkowski, M., Niekrasz, J., & Hauswirth, M. (2016). Assessing Problem-Solving Process At Scale. In *Proceedings of the Third (2016) ACM Conference on Learning @ Scale* (pp. 245–248). New York, NY, USA: ACM. https://doi.org/10.1145/2876034.2893425

Grover, S., Cooper, S., & Pea, R. (2014). Assessing Computational Learning in K-12. In *Proceedings of the 2014 Conference on Innovation & Technology in Computer Science Education* (pp. 57–62). New York, NY, USA: ACM. https://doi.org/10.1145/2591708.2591713

Grover, S., Pea, R., & Cooper, S. (2015). Designing for deeper learning in a blended computer science course for middle school students. *Computer Science Education*, *25*(2), 199–237. https://doi.org/10.1080/08993408.2015.1033142

Gutierrez, F. J., Simmonds, J., Hitschfeld, N., Casanova, C., Sotomayor, C., & Penã-Araya, V. (2018). Assessing software development skills among K-6 learners in a project-based workshop with scratch. In *Proceedings of the 40th International Conference on Software Engineering: Software Engineering Education and Training* (pp. 98–107). https://doi.org/10.1145/3183377.3183396

Guzdial, M. (2008). Education paving the way for computational thinking. *Communications of The ACM*, *51*(8), 25–27. https://doi.org/https://doi.org/10.1145/1378704.1378713

Haythornthwaite, C., & Andrews, R. (2011). *E-Learning theory and practice*. London, UK: Sage Publications.

Hershkovitz, A., Sitman, R., Israel-Fishelson, R., Eguíluz, A., Garaizar, P., & Guenaga, M. (2019). Creativity in the acquisition of computational thinking. *Interactive Learning Environments*, *27*(5–6), 628–644. https://doi.org/10.1080/10494820.2019.1610451

Hong, Q. N., Pluye, P., Bujold, M., & Wassef, M. (2017). Convergent and sequential synthesis designs : implications for conducting and reporting systematic reviews of qualitative and quantitative evidence. *Systematic Reviews*, 1–14. https://doi.org/10.1186/s13643-017-0454-2

Hoover, A. K., Barnes, J., Fatehi, B., Moreno-León, J., Puttick, G., Tucker-Raymond, E., & Harteveld, C. (2016). Assessing Computational Thinking in Students' Game Designs. In *Proceedings of the 2016 Annual Symposium on Computer-Human Interaction in Play Companion* (pp. 173–179). New York, NY, USA: ACM. https://doi.org/10.1145/2968120.2987750

Jacob, S. R., & Warschauer, M. (2018). Computational Thinking and Literacy. *Journal of Computer Science Integration*, *1*(1). https://doi.org/10.26716/jcsi.2018.01.1.1

Jenkins, H. (2006). Confronting the Challenges of Participatory Culture: Media Education for the 21st Century. An Occasional Paper on Digital Media and Learning. *John D. and Catherine T. MacArthur Foundation*, *2*(2), 97–113.

Kalantzis, M., Cope, W., Chan, E., & Dalley-Trim, L. (2016). *Literacies* (2nd ed). Cambridge: Cambridge University Press.

Kerekes, J., Jang, E., & Peterson, S. S. (2014). Assessing Multiliteracies : Mismatches and Opportunities Assessing Multiliteracies : Mismatches and Opportunities University of Massachusetts Amherst, (May). https://doi.org/10.20360/G21G6W

Kirwan, C., Costello, E., & Donlon, E. (2018). Computational thinking and online learning: A systematic literature review. In *Proceedings of the European Conference on e-Learning, ECEL* (pp. 650–657).

Kitchenham, B., & Ebse, C. (2007). Guidelines for performing Systematic Literature Reviews in Software Engineering Executive summary.

Knight, S., & Littleton, Simon Buckingham Shum, K. (2014). Epistemology, Assessment, Pedagogy: Where Learning Meets Analytics in the Middle Space.

Journal of Learning Analytics, *1*(2), 23–47.

Mangaroska, K., & Giannakos, M. (2019). Learning Analytics for Learning Design: A Systematic Literature Review of Analytics-Driven Design to Enhance Learning. *IEEE Transactions on Learning Technologies*, *12*(4), 516–534. https://doi.org/10.1109/TLT.2018.2868673

Mangaroska, K., Sharma, K., Giannakos, M., Tr\aetteberg, H., & Dillenbourg, P. (2018). Gaze Insights into Debugging Behavior Using Learner-Centred Analysis. In *Proceedings of the 8th International Conference on Learning Analytics and Knowledge* (pp. 350–359). New York, NY, USA: Association for Computing Machinery. https://doi.org/10.1145/3170358.3170386

Mangaroska, K., Sharma, K., Giannakos, M., Trætteberg, H., & Dillenbourg, P. (2018). Gaze insights into debugging behavior using learner-Centred analysis. *ACM International Conference Proceeding Series*, 350–359. https://doi.org/10.1145/3170358.3170386

Martinez-Maldonado, R., Echeverria, V., Santos, O. C., Dos Santos, A. D. P., & Yacef, K. (2018). Physical learning analytics: A multimodal perspective. *ACM International Conference Proceeding Series*, 375–379. https://doi.org/10.1145/3170358.3170379

Martinez-Maldonado, R., Echeverria, V., Santos, O. C., Santos, A. D. P. Dos, & Yacef, K. (2018). Physical Learning Analytics: A Multimodal Perspective. In *Proceedings of the 8th International Conference on Learning Analytics and Knowledge* (pp. 375–379). New York, NY, USA: Association for Computing Machinery. https://doi.org/10.1145/3170358.3170379

Mello, S. K. D. (2014). Emotional Learning Analytics. In *Handbook of learning analytics* (pp. 115–127). https://doi.org/10.18608/hla17.010

Millecamp, M., Gutiérrez, F., Charleer, S., Verbert, K., & De Laet, T. (2018). A Qualitative Evaluation of a Learning Dashboard to Support Advisor-Student Dialogues. In *Proceedings of the 8th International Conference on Learning Analytics and Knowledge* (pp. 56–60). New York, NY, USA: Association for Computing Machinery. https://doi.org/10.1145/3170358.3170417

Mitri, D. Di, Schneider, J., Klemke, R., Specht, M., & Drachsler, H. (2019). Read between the lines: An annotation tool for multimodal data for learning. In *ACM International Conference Proceeding Series* (pp. 51–60). https://doi.org/10.1145/3303772.3303776

Moissa, B., Gasparini, I., & Kemczinski, A. (2015). A systematic mapping on the learning analytics field and its analysis in the massive open online courses context. *International Journal of Distance Education Technologies (IJDET)*, *13*(3), 1–24.

Montaño Juanand Mondragón, C. and T.-M. H. and O. L. (2019). Learning Analytics on the Gamified Assessment of Computational Thinking. In M. Tlili Ahmedand Chang (Ed.), *Data Analytics Approaches in Educational Games and Gamification Systems* (pp. 95–109). Singapore: Springer Singapore. https://doi.org/10.1007/978-981-32-9335-9_5

Moreno León, J., Robles, G., & Román González, M. (2015). Dr. Scratch: Automatic Analysis of Scratch Projects to Assess and Foster Computational Thinking. *RED: Revista de Educación a Distancia*, (46), 23. Retrieved from http://www.um.es/ead/red/46

Nasar, Z., Jaffry, S. W., & Malik, M. K. (2019). Textual keyword extraction and summarization: State-of-the-art. *Information Processing & Management*, *56*(6), 102088. https://doi.org/https://doi.org/10.1016/j.ipm.2019.102088

Ndukwe, I. G., & Daniel, B. K. (2020). Teaching analytics, value and tools for teacher data literacy: a systematic and tripartite approach. *International Journal of Educational Technology in Higher Education*, *17*(1), 1–31. https://doi.org/10.1186/s41239-020-00201-6

New London Group. (2000). Multiliteracies: Literacy Learning and the Design of Social Futures. In B. Cope & M. Kalantzis (Eds.), *Multiliteracies: Literacy Learning and the Design of Social Futures* (pp. 9–38). London: Routledge. Retrieved from https://books.google.ca/books?id=7dwzLAEWr78C

O'Mara-Eves, A., Thomas, J., McNaught, J., Miwa, M., & Ananiadou, S. (2015). Using text mining for study identification in systematic reviews: a systematic review of current approaches. *Systematic Reviews*, *4*(1), 5. https://doi.org/10.1186/2046-4053-4-5

Ochoa, X. (2017). Multimodal learning analytics. In *Handbook of learning analytics* (pp. 129–141).

Oldfield, A., Broadfoot, P., Sutherland, R., & Timmis, S. (2012). *Assessment in a Digital Age: A research review*. *Technology Enhanced Assessment: Review of the Literature*. Bristol. Retrieved from http://www.bristol.ac.uk/media-library/sites/education/documents/researchreview.pdf

Papert, S. (1996). An exploration in the space of mathematics educations. *International Journal of Computers for Mathematical Learning*, *1*(1), 95–123. https://doi.org/10.1007/BF00191473

Pishtari, G., Rodríguez-Triana, M. J., Sarmiento-Márquez, E. M., Pérez-Sanagustín, M., Ruiz-Calleja, A., Santos, P., … Väljataga, T. (2020). Learning design and learning analytics in mobile and ubiquitous learning: A systematic review. *British Journal of Educational Technology*, *51*(4), 1078–1100. https://doi.org/10.1111/bjet.12944

Portelance, D. J., & Bers, M. U. (2015). Code and Tell: Assessing Young Children's Learning of Computational Thinking Using Peer Video Interviews with ScratchJr. In *Proceedings of the 14th International Conference on Interaction Design and Children* (pp. 271–274). New York, NY, USA: ACM. https://doi.org/10.1145/2771839.2771894

Quadir, B., Chen, N. S., & Isaias, P. (2020). Analyzing the educational goals, problems and techniques used in educational big data research from 2010 to 2018. *Interactive Learning Environments*, *0*(0), 1–17. https://doi.org/10.1080/10494820.2020.1712427

Roman-Gonzalez, M., Perez-Gonzalez, J.-C., & Jimenez-Fernandez, C. (2017). Which cognitive abilities underlie computational thinking? Criterion validity of the Computational Thinking Test. *COMPUTERS IN HUMAN BEHAVIOR*, *72*, 678–691. https://doi.org/10.1016/j.chb.2016.08.047

Román-González, M., Pérez-González, J.-C., Moreno-León, J., & Robles, G. (2018). Can computational talent be detected? Predictive validity of the Computational Thinking Test. *International Journal of Child-Computer Interaction*, *18*, 47–58. https://doi.org/10.1016/J.IJCCI.2018.06.004

Roman Gonzalez, M. (2015). COMPUTATIONAL THINKING TEST: DESIGN GUIDELINES AND CONTENT VALIDATION. In GomezChova, L and LopezMartinez, A and CandelTorres, I (Ed.), *EDULEARN15: 7TH INTERNATIONAL CONFERENCE ON EDUCATION AND NEW LEARNING TECHNOLOGIES* (pp. 2436–2444). LAURI VOLPI 6, VALENICA, BURJASSOT 46100, SPAIN: IATED-INT ASSOC TECHNOLOGY EDUCATION & DEVELOPMENT.

Romero, M., Lepage, A., & Lille, B. (2017). Computational thinking development through creative programming in higher education. *International Journal of Educational Technology in Higher Education*, *14*(42), 15. https://doi.org/10.1186/s41239-017-0080-z

Rowe, E., Asbell-Clarke, J., Cunningham, K., & Gasca, S. (2017). Assessing implicit computational thinking in Zoombinis gameplay: Pizza pass, fleens & bubblewonder abyss. In *CHI PLAY 2017 Extended Abstracts - Extended Abstracts Publication of the Annual Symposium on Computer-Human Interaction in Play* (pp. 195–200). Amsterdam, Netherlands: ACM. https://doi.org/10.1145/3130859.3131294

Schick, A., Morlock, D., Amma, C., Schultz, T., & Stiefelhagen, R. (2012). Vision-based handwriting recognition for unrestricted text input in mid-air. In *of the 14th ACM International Conference on Multimodal Interaction (ICMI '12)* (pp. 217–220). New York, NY, USA. Retrieved from http://dx.doi.org/10.1145/2388676.2388719

Schilder, E., Lockee, B., & Saxon, D. (2016). The Challenges of Assessing Media Literacy Education. *Journal of Media Literacy Education*, *8*(1), 32–48.

Schlömer, T., Poppinga, B., Henze, N., & Boll, S. (2008). Gesture recognition with a Wii controller. In *Proceedings of the 2nd International Conference on Tangible and Embedded Interaction (TEI '08)* (pp. 11–14). Retrieved from http://dx.doi.org/10.1145/1347390.1347395

Schneider, J., Börner, D., Van Rosmalen, P., & Specht, M. (2015). Augmenting the senses: A review on sensor-based learning support. *Sensors (Switzerland)*, *15*(2), 4097–4133. https://doi.org/10.3390/s150204097

Shepard, L. A. (2000). The Role of Assessment in a Learning Culture. *Educational Researcher*, *29*(7), 4–14. https://doi.org/10.3102/0013189X029007004

Shorfuzzaman, M., Hossain, M. S., Nazir, A., Muhammad, G., & Alamri, A. (2019). Harnessing the power of big data analytics in the cloud to support learning analytics in mobile learning environment. *Computers in Human Behavior*, *92*, 578–588. https://doi.org/https://doi.org/10.1016/j.chb.2018.07.002

Siemens, G., & Baker, R. (2012). Learning analytics and educational data mining: towards communication and collaboration. In *In Proceedings of the 2nd International Conference on Learning Analytics and Knowledge (ACM)* (pp. 252–254). Vancouver, British Columbia, Canada. https://doi.org/https://doi.org/10.1145/2330601.2330661

Siemens, G., & Long, P. (2011). Penetrating the fog: Analytics in learning and education. *Educause Review*, *46*(5), 30.

Sin, K., & Muthu, L. (2015). Application of Big Data in Education Data Mining and Learning Analytics – a Literature Review. *ICTACT Journal on Soft Computing*, *05*(04), 1035–1049. https://doi.org/10.21917/ijsc.2015.0145

Srinivas, M., Roy, M., Sagri, J. N., & Kumar, V. (2018). Assessing Scratch Programmers' Development of Computational Thinking with Transaction-Level Data. In S. Chakraverty, M. Sanjay, & A. Goel (Eds.), *Towards Extensible and Adaptable Methods in Computing* (pp. 398–407). Waterloo, Canada: Springer. https://doi.org/10.1007/978-981-13-2348-5

Srinivas Milan J.and Roy, M. M. and S. J. N. and K. V. (2018). Assessing Scratch Programmers' Development of Computational Thinking with Transaction-Level Data. In A. and M. S. Chakraverty Shampaand Goel (Ed.), *Towards Extensible and Adaptable Methods in Computing* (pp. 399–407). Singapore: Springer Singapore. https://doi.org/10.1007/978-981-13-2348-5_30

Sweeney, T., West, D., Groessler, A., Haynie, A., Higgs, B., Macaulay, J., … Yeo, M. (2017). Where's the transformation? Unlocking the potential of technology-enhanced assessment. *Teaching and Learning Inquiry*, *5*(1), 1–16. https://doi.org/10.20343/5.1.5

Tang, X., Yin, Y., Lin, Q., Hadad, R., & Zhai, X. (2020). Assessing computational thinking: A systematic review of empirical studies. *Computers and Education*, *148*(January), 103798. https://doi.org/10.1016/j.compedu.2019.103798

Vieira, C., Parsons, P., & Byrd, V. (2018). Visual learning analytics of educational data: A systematic literature review and research agenda. *Computers & Education*, *122*, 119–135. https://doi.org/https://doi.org/10.1016/j.compedu.2018.03.018

Vygotsky, L. S. (1978). *Mind in society: The development of higher mental processes*. Cambridge, Mass: Harvard University Press.

Weese, J. L. (2016a). Mixed Methods for the Assessment and Incorporation of Computational Thinking in K-12 and Higher Education. In *Proceedings of the 2016 ACM Conference on International Computing Education Research* (pp. 279–280). New York, NY, USA: Association for Computing Machinery. https://doi.org/10.1145/2960310.2960347

Weese, J. L. (2016b). Mixed Methods for the Assessment and Incorporation of Computational Thinking in K-12 and Higher Education. In *Proceedings of the 2016 ACM Conference on International Computing Education Research* (pp. 279–280). New York, NY, USA: ACM. https://doi.org/10.1145/2960310.2960347

Weintrop, D, Beheshti, E., Horn, M. S., Orton, K., Trouille, L., Jona, K., & Wilensky, U.

(2014). Interactive Assessment Tools for Computational Thinking in High School STEM Classrooms. *Lecture Notes of the Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering, LNICST*, *136 LNICST*, 22–25. https://doi.org/10.1007/978-3-319-08189-2_3

Weintrop, David, Beheshti, E., Horn, M., Orton, K., Jona, K., Trouille, L., & Wilensky, U. (2016). Defining Computational Thinking for Mathematics and Science Classrooms. *Journal of Science Education and Technology*, *25*(1), 127–147. https://doi.org/10.1007/s10956-015-9581-5

Werner, L., Denner, J., Campe, S., & Kawamoto, D. C. (2012). The Fairy Performance Assessment: Measuring Computational Thinking in Middle School. In *Proceedings of the 43rd ACM Technical Symposium on Computer Science Education* (pp. 215–220). New York, NY, USA: ACM. https://doi.org/10.1145/2157136.2157200

Westera, W. (2010). Technology-enhanced learning: review and prospects. *Serdica J Comput*, *4*(2), 159–182.

Williamson, B. (2017). Moulding student emotions through computational psychology : affective learning technologies and algorithmic governance, *54*(4), 267–288.

Wing, J. M. (2006). Computational Thinking. *Communications of the ACM*, *49*(3), 33–35.

Worsley. (2011). What ' s an Expert ? Using learning analytics to identify emergent markers of expertise through automated speech , sentiment and sketch analysis .

Worsley, M. (2014). Multimodal Learning Analytics as a Tool for Bridging Learning Theory and Complex Learning Behaviors. In *Proceedings ofthe 2014 ACMworkshop on Multimodal Learning Analytics Workshop and Grand Challenge - MLA '14. ACM* (pp. 1–4). New York, USA. https://doi.org/https://doi.org/10.1145/2666633.2666634

Worsley, M. (2018). Multimodal learning analytics' past, present, and, potential futures. In *CEUR Workshop Proceedings* (pp. 1–16). Aachen, Germany. Retrieved from http://crossmmla.org/wp-content/uploads/2018/ 02/CrossMMLA2018

Worsley, M., & Blikstein, P. (2010). *Toward the Development of Learning Analytics : Student Speech as an Automatic and Natural Form of Assessment*.

Worsley, M., & Blikstein, P. (2013). Towards the Development of Multimodal Action Based Assessment. In *Proceedings of the third international conference on learning analytics and knowledge* (pp. 94–101).

Worsley, M., & Blikstein, P. (2014). Analyzing Engineering Design through the Lens of Computation. *Journal of Learning Analytics*, *1*(2), 151–186.

Yadav, A., Burkhart, D., Moix, D., Snow, E., Bandaru, P., & Clayborn, L. (2015). *Sowing the Seeds: A Landscape Study on Assessment in Secondary Computer Science Education*. New York, NY, USA: Computer Science Teacher Association. Retrieved from www.csta.acm.org

Zhang, L., & Nouri, J. (2019). A systematic review of learning computational thinking through Scratch in K-9. *Computers & Education*, *141*, 103607.

https://doi.org/10.1016/j.compedu.2019.103607

Curriculum Vitae

Name: Negar Shabihi

Education: MA in Education, Western University, Canada, (2022)
MSc in Computer Engineering, Tehran University, Iran, (2016)
Bachelor of Computer Engineering, Tehran University, Iran,(2013)

Recent Awards:

IEEE TCLT Student Travel Award for ICALT, (2021)
AER Scholarship for Literacy Studies in Education, (2020)
AER Scholarship for Literacy Studies in Education, (2019)

Related Work/Experience:

Data Science and Engineering Intern
FinnAI, Canada, (2021-current)

Research Assistant,
Education Faculty, Western University, Canada (2019-2021)

Software Developer and Data Analyst,
Sapna Company, Iran (2015-2019)

Researcher and Data Analyst,
Iran Telecommunication Research Center (ITRC), Iran (2017)

Researcher and Data Analyst,
Science Academy, Iran -Investigating Females' role in Engineering (2016)

Teacher Assistant,
Data Mining & IT management Courses, Tehran University, (2015-2016)

Research Assistant,
Multi-Agent Systems Lab, Tehran University, Iran (2013-2016)

Robotics and Math Teacher,
different schools and organizations, Iran (2009 - 2014)

Publications:

- **N. Shabihi**, M, S, Kim, "Data-Driven Understanding of Computational Thinking Assessment: A Systematic Literature Review", ECEL-2021 (Accepted)
- **N. Shabihi**, M, S, Kim, "Big Data Analytics in Education: A Data-Driven Literature Review", IEEE-ICALT-2021, 154-156, 2021.
- **N. Shabihi**, F. Taghiyareh, "The Relationship between Gender and Game dynamics in e-learning environments: an empirical investigation", ECGBL-2019, pp. 574-XXIII, 2019.
- **N. Shabihi**, F. Taghiyareh, MH. Abdoli, "Enhancement of educational games based on personality type indicators," Journal of Information & Communication Technology, 9(3), pp. 37-45, 2018.
- **N. Shabihi**, F. Taghiyareh, "Toward a Personalized Game-Based Learning Environment Using Personality Type Indicators," ECEL-2017, pp. 476-483, 2017.
- S. Alvandkoohi, F. Taghiyareh, **N. Shabihi**, "Towards Game Element Personalization Using Player's Feeling and Personality Type," ECGBL-2017, pp. 9-13, 2017.

- **N. Shabihi**, F. Taghiyareh, MH. Abdoli, "Analyzing the effect of game-elements in e-Learning environments through MBTI-based personalization," IEEE-IST-2016, pp. 612-618, 2016