The measurement and analysis of team cohesion in technology-mediated environments using learning analytics

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Declaration of Authorship

I, Andrew Zamecnik, declare that this thesis titled, 'The measurement and analysis of team cohesion in technology-mediated environments using learning analytics' and the work presented in it are my own. I confirm that:

- the thesis comprises only my original work towards the Doctor of Philosophy except where indicated in the preface;
- due acknowledgment has been made in the text to all other material used; and
- the thesis is fewer than the maximum word limit in length, exclusive of tables, maps, bibliographies and appendices as approved by the Research Higher Degrees Committee.

Signed:



Date:
13-01-2023

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Abstract

In recent years, the world has experienced many disruptive changes leading to significant transformations in how students learn. Disruptions such as COVID-19 have led to the increasing uptake of learners enrolling for online or blended education, including technology-mediated environments that involve collaborative learning experiences where learners work together as a team to solve complex problems and gain crucial skills. This is also driven by the demands of the modern working environment pushed by industry and governments to be innovative and competitive.

An important factor for successful teams is maintaining a consistent level of cohesion throughout their studies. Cohesion in teams is crucial for achieving better learning and performance outcomes. However, research that examines the temporality of cohesion in teams within technology-mediated learning contexts is limited. Given that team cohesion is an emergent state that changes over time, analytical-based approaches informed by temporal data are required to capture the complexities of cohesion. Moreover, there is limited to what extent learning constructs, such as feedback, engagement and performance align with the changing cohesive perceptions of teams about themselves. The lack of insights into student learning and team interactions in technology-mediated environments presents a challenge for educators to monitor teamwork, further exacerbating the risk to team cohesion and overall success in learning. Learning analytics can play a crucial role here by analysing observational behaviours of team learning, which can indicate the bearings of cohesion and help to bridge theory and practice. It is an opportunity for educators to analyse, understand and monitor cohesion to help learners in collaborative contexts.

This thesis aims to investigate and analyse the factors influencing cohesion in collaborative learning within technology-mediated contexts. It focuses on four key research objectives: developing an analytics-based measure to evaluate team cohesion using trace data, exploring the relationship between learning constructs and cohesive perceptions, investigating the actions of team members in promoting or

hindering cohesion and designing a learning analytics dashboard (LAD) to provide insights and support for teams and educators.

The first aim is to present a literature review on cohesion in such contexts, summarising current research and providing guidance for future work. This aim will aid researchers and educational stakeholders in scaffolding future work on the topic. The second aim is to create a way to measure cohesion using data from learners' actions, without relying on surveys. This method will use observational indicators to understand how the group works together and how cohesion develops over time. The third aim is to examine how the actions of team members during learning can indicate their level of cohesion and influence the team's ability to reach consensus or disagreement based on their shared perceptions of cohesion. The final aim of this thesis includes the development of a learning analytics dashboard (LAD) that students can use to monitor and regulate their learning in technology-mediated environments. This addresses the need for supporting students in these settings and can be integrated with analytics-based measures of team cohesion to provide insights to both teams and educators. The LAD and analytics-based measures can be combined in the future for comprehensive team dashboards.

The implications of this work will be valuable for future research in understanding team behaviours, including cohesion, and optimising learning outcomes through the use of LADs in technology-mediated learning settings.

The thesis covers the overall measurement and analysis of team cohesion using learning analytics to address each research aim. The results presented in this thesis will shed light on how team cohesion forms and evolves in learning experiences. These results will be useful for instructors and designers to consider when supporting teams and their learning in technology-mediated environments.

Publication

Publications arising from the time of this thesis.

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Abbreviations

AI	Artificial Intelligence
CLA	Collaborative Learning Analytics
CSCL	Computer-Supported Collaborative Learning
DBR	Design-based Research
EDM	Educational Data Mining
ENA	Epistemic Network Analysis
IRR	Inter-rater Agreement
ITS	Intelligent Tutoring Systems
K-12	Kindergarten Through Twelfth
LA	Learning Analytics
LAD	Learning Analytics Dashboard
LATUX	Learning Awareness Tools - User Experience
LMS	Learning Management System
MOOC	Massive Open Online Course
PEOU	Perceived Ease of Use
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PU	Perceived Usefulness
SLR	Systematic Literature Review
SVD	Singular Value Decomposition
TAM	Technology Acceptance Model
TML	Technology-Mediated Learning
VET	Vocational Educational Training
WIL	Work-Integrated Learning

Chapter 1

Introduction

In the unprecedented age of disruption caused by climate change, the global pandemic and the relentless advancement of artificial intelligence (AI), there is a growing need for worker-driven learning and collaboration in Australia to innovate and drive competitive advantage in the modern workplace (Gallagher, 2021; O.E.C.D., 2021). Employers recognise the erosion of worker skills, capability and expertise due to the rapidly changing roles and the nature of work. Recent studies show that one in two Australian workers do not necessarily engage in lifelong learning, which diminishes their potential for innovation in the workplace (Gallagher, 2021). The findings align with the previous government report on Australia's vision for 2030 innovation and science development (Innovation & Australia, 2017), foreshadowing the importance of preparing the future workforce for rapidly changing roles and the nature of work. Changing roles and nature of work are mainly digitally dependent and integrated, occurring in online platforms with a social element. The workforce requires a reimagination in teaching and education to ensure that new employees are better equipped to deal with these changes (O.E.C.D., 2021). Changes include becoming more diverse and inclusive, adopting more flexible work practices and becoming less hierarchical (Gallagher, 2021; Innovation & Australia, 2017; "National Commitee for Information and Communication Sciences", 2019). In that sense, teamwork and collaboration are increasingly valued within firms and

across industries to improve productivity and competitiveness. Therefore, preparing the next generation of learners aligned with these skills is crucial for the needs of governments, research institutions and industries.

Major online educational providers are helping to address such critical skills gaps by facilitating work-integrated learning (WIL) environments to prepare the next generation of learners for the future of work (Ferns et al., 2015; Tan, 2021). In these environments, seasoned professionals regularly support learners working collaboratively on real-life problems (Cooper et al., 2010b). For teams to perform well in a collaborative environment, they must be cohesive (Beal et al., 2003; Evans & Dion, 1991; Grossman et al., 2021). Throughout the years, cohesion has been commonly defined as the social bonding between people and their shared task commitments in achieving their goals or united in working together (Carron et al., 1985; Festinger, 1950; Mullen & Copper, 1994; Seashore, 1954). Cohesion allows teams to be productive, enhance motivation, limit social loafing, support their team members, trust and exchange feedback in groups (Edmondson & Lei, 2014; Karau & Williams, 1997; Schachter et al., 1951; Slone et al., 2015). Teams that maintain high levels of cohesion have been shown to outperform teams with low cohesion for a given task (Beal et al., 2003; Carron et al., 2002; Castaño et al., 2013; Evans & Dion, 1991; Mullen & Copper, 1994).

Measuring team cohesiveness can be challenging, and researchers have explored various approaches to address this issue (Treuer et al., 2018). One way to classify these approaches is by their level of research involvement, which can be obtrusive or unobtrusive. Obtrusive approaches involve direct research involvement that interrupts the team, whereas unobtrusive measures minimise research involvement by allowing the team to conduct their work uninterrupted. For example, obtrusive approaches may involve participants answering questions from surveys or conducting focus groups where participants are asked about their experiences. In contrast, unobtrusive approaches can include analysing real-time or archival data such as digital communication logs or task completion data to determine how well teams work together.

Despite the usefulness of obtrusive approaches such as surveys, these instruments are limited in capturing the temporal development of cohesion and the complex nuances that form in the group. Cohesion is a mutable construct that emerges over time (Kozlowski & Chao, 2012), and as a result, researchers have called for new assessment models to monitor cohesion and support teams (Salas et al., 2015). Unobtrusive measures offer promise in the temporal analysis of cohesion. However, research on new temporal methods for measuring cohesion is limited due to knowledge capability and data collection (Kozlowski & Chao, 2018).

While observing team behaviours is challenging, prominent researchers in team dynamics (Kozlowski & Chao, 2018; Kozlowski, 2015; Kozlowski & Klein, 2000) advocate the practice of temporal methodologies for analysing log data generated by teams to measure and analyse how cohesion emerges. Cohesion is an emergent state that develops over time, representing the synchrony of different cyclical, reciprocal or repetitive behavioural interactions. These representations can be shown by team members' behavioural interactions when working together on a task (Santoro et al., 2015). Forsyth (2021) has suggested that observable qualities of a group may serve as a proxy of the group's unity by being intuited from direct observations of the group's behaviour. Namely, the level of interaction, group synchrony and similarities in behaviours may serve as indirect indicators of cohesion (Swol & Kane, 2019). Salas (2015) argues that combining obtrusive and unobtrusive approaches will reveal more significant insights into cohesion instead of preferring one approach to the other.

There is an opportunity to explore the use of analytical methods in other disciplines to study team cohesion. In the educational context regarding the community of inquiry framework, researchers have examined cohesion through social presence (Dado & Bodemer, 2017). One of the typical approaches to measure cohesion on the social level is through social network analysis (Dascalu et al., 2018). However, the literature examining the team cohesion of small groups in education based on their task cohesion is scarce and not consolidated in the collaborative learning context. Small groups are fundamentally different from communities as they have increased accountability, relationships, contributions and dialogue (Cherney

et al., 2018). There is limited knowledge regarding the conceptualisation of cohesion, methodological approaches used, and the learning factors impacting or facilitating cohesion in educational settings. These gaps are compounded by the lack of studies examining data-driven attempts using log data to measure and analyse cohesion over time. Studies that have identified connections between the behaviours of cohesion and collaborative learning are limited. The problem of using technology, such as dashboards that capture the interactions of teams (i.e., team members and leaders) and help monitor workflow processes to support team cohesion, is not well understood. The need for the consolidation of these studies is crucial, as cohesion in education can have a positive impact on the quality of learning in groups (Xie et al., 2019). For instance, it can help support collaboration and communication, reduce conflicts and invoke a sense of responsibility. Overall, addressing team cohesion helps to create a positive learning environment where teams feel supported and motivated to work together. Promoting these skills can enhance the quality of learning in teams and help them to achieve their educational goals. Addressing these important research gaps will help researchers and educators to understand how cohesion manifests in these environments.

Despite the importance of cohesion in small groups, research exploring the interplay between cohesion and learning constructs in technology-mediated learning is limited (Zamecnik et al., 2022c). This lack of insight hampers the ability of researchers and instructors to provide pedagogical interventions to support or enhance cohesion and performance in small groups. Collaborative learning analytics (CLA) provides a promising approach for generating actionable group insights that can help instructors and teams improve their collaboration and learning (Martinez-Maldonado et al., 2021). However, the application of CLA to conjoin mental processes that teams externalize through their learning engagement and behaviour for cohesion remains largely unexplored.

As a data-driven approach, learning analytics (LA) has been used to optimise students' learning and help provide insights for educators and researchers to support learners pedagogically (Siemens & Long, 2011). While there are several gaps

in understanding, measuring, identifying, and supporting team cohesion in collaborative learning environments, the rise of LA offers an opportunity to help bridge theory and practice to address the concerns (Bannert et al., 2017; Siemens, 2013). LA allows for measuring and analysing observational behaviours in an educational setting through the learner's trace data (Siemens & Long, 2011), which are time-stamped actions of learners interacting with their environment (Winne, 2020). Trace data from the process level may represent the bearings of cohesion. Temporal analysis can assist in theory-advancing studies by understanding process-related behaviours (Knight et al., 2017; Lämsä et al., 2021). Process data has given rise to LA tools, such as student-facing dashboards, that allow learners to monitor and regulate their learning over time through feedback (Bodily & Verbert, 2017). Given the benefits of using dashboards, they present opportunities to support teams and their cohesion in collaborative learning. For teams to be cohesive, they need high levels of shared commitment to complete a goal (Carron et al., 1985). Dashboards in collaborative environments are one way to illustrate these levels of shared commitment to how team members are completing their tasks together (Zamecnik et al., 2022c). The dashboard can provide feedback to teams by collecting data traces of such behaviours and informing them on their workflow processes, which are crucial for performance (Marks et al., 2001). Therefore, LA presents an opportunity to solve the disparities facing researchers and educators when supporting teams in collaborative learning to enhance their performance.

1.1 Argumentation, motivation and novelty

The thesis contains four research aims to address the gaps identified in this chapter. The research aims and associated research questions addressed in this thesis are outlined in Fig 1.1. In the next section, each research aim contains a thread on the argumentation, motivation, and novelty relevant to the research field.

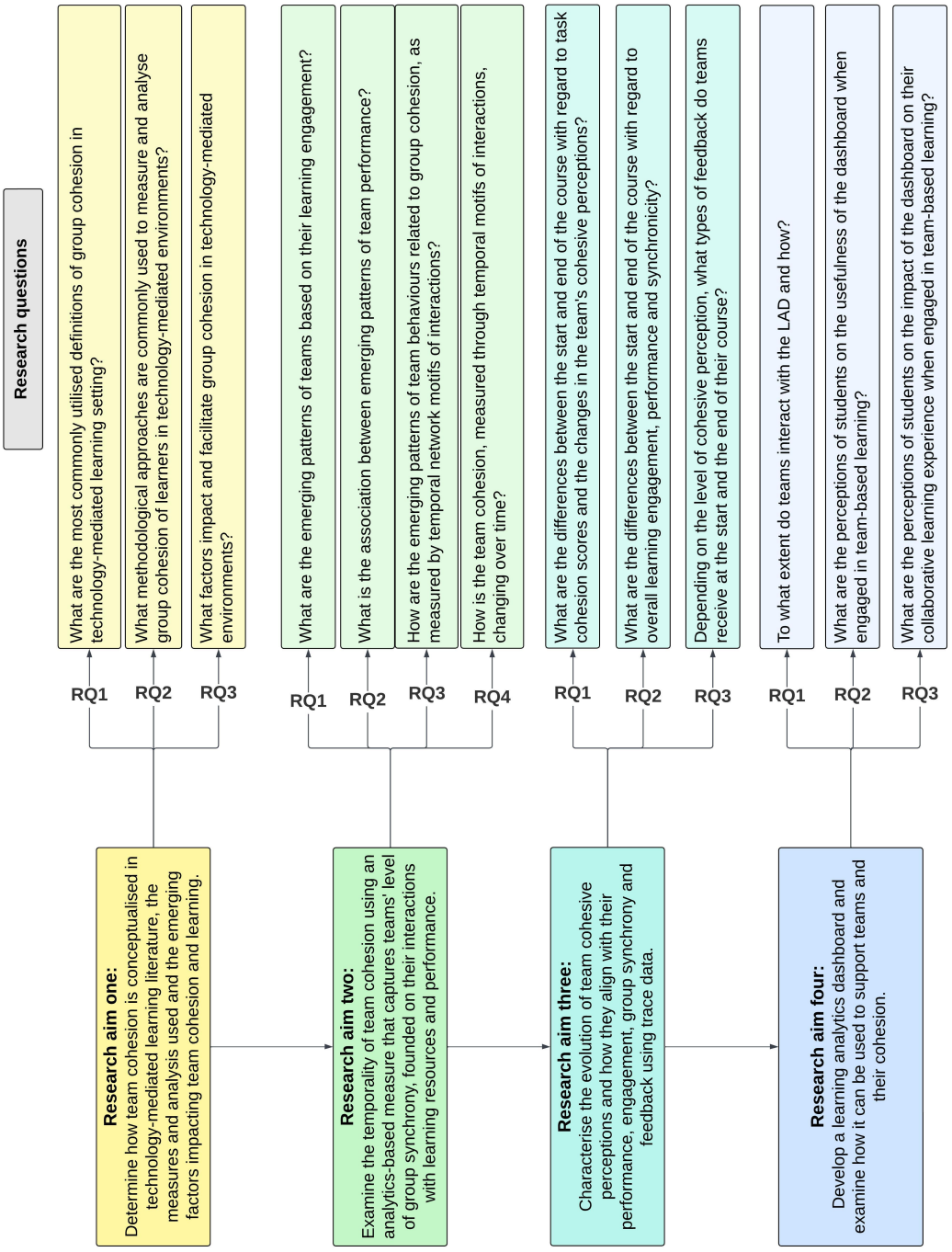


FIGURE 1.1: Consolidated research aims and questions in this thesis. The arrows between the aims imply a sequence in the text.

Research aims one

It is becoming increasingly important to understand how collaborative processes, such as group cohesion, unfold in multi and interdisciplinary teams. Changing

nature of work requires a technologically literate and collaborative-ready workforce (Bakhshi et al., 2017; Hajkowicz et al., 2016). The 'work from home' experiment due to the pandemic had a profound impact on the responsibility of the worker in the way they conducted virtual collaboration, such as handling personal obligations, spending more time coordinating and remaining optimistic that the culture of companies is changing for the better (PwC, 2020). Consequences of these changes have drastically impacted the norms of work, by driving the workforce to rapidly upskill or operate in environments that often represent a departure from what was accepted as a norm. With these current trends, the organisational landscapes are transforming due to emerging technologies and require organisations to anticipate the shifting behaviours of stakeholders and technologies to remain competitive (Parry & Battista, 2019; Verhoef et al., 2021). Changes include becoming more diverse and inclusive, adopting more flexible work practices and becoming less hierarchical (Spurk & Straub, 2020; Waizenegger et al., 2020). In that sense, teamwork and collaboration will be increasingly valued, whereas innovation within firms and across industries becomes essential to improving productivity and competitiveness.

In collaborative learning, cohesion in small groups leads to the development of greater trust in sharing ideas and information that further promotes learning (Edmondson, 1999; Kreijns et al., 2003; Williams et al., 2006). However, facilitating cohesion in technology-mediated contexts is argued to be challenging compared to face-to-face settings, primarily due to the absence of social cues to help forecast behaviour. As a result, this may impact the way cohesion is established and maintained (Gonzales et al., 2010; Kreijns et al., 2003; Shin & Song, 2011). Therefore, innovative approaches and strategies must be sought to identify and understand how groups or teams can enhance cohesion in technology-mediated environments.

Given the importance of group and team cohesion in general and technology-mediated environments, a systematic literature review was conducted to understand how cohesion is defined, measured, facilitated and impacts learners studying

in collaborative settings. Articles were reviewed that measured and facilitated cohesion, such as the design of technological tools and interventions to improve cohesion and collaborative learning validated with surveys or event log data to achieve this review's goal. Second, the findings are discussed regarding the methodologies used and the factors that influence or substantiate cohesion, learning performance and the progression of research. Finally, the knowledge gaps are discussed, and the design implications and future work required for further development are addressed.

Research aims two

Most approaches to measuring cohesion are based on self-reports, such as the widely used instrument by Carron and colleagues (1985), used to measure cohesion in various disciplines. However, self-reports have underlying issues such as the risk of bias, completion rates, inherent intrusive nature, and static measurements (Cook et al., 2002; Visser et al., 2000). Kozlowski and Chao (2012) point out the limitations of the measuring processes of cohesion. It is recognised that the true fidelity of measuring processes of cohesion faces significant limitations using surveys. As a result, there have been calls for novel ways of measuring cohesion that takes into account the temporal nature of the construct (Kozlowski & Chao, 2018; Salas et al., 2015). Although, the literature that examines cohesion as a temporal process is significantly limited, focusing mainly on understanding principles and mechanisms that lead to higher cohesion in groups or teams from their learning activities (Zamecnik et al., 2022c).

Research on the cohesion of small groups in technology-mediated learning mainly focuses on evaluating educational methods centred around static, self-reported data collection instead of trace data (Zamecnik et al., 2022c). Although providing invaluable insights for understanding cohesion in learning settings, the nature of commonly applied approaches does not necessarily provide a means for understanding cohesion as it unfolds. One way to address the measurement and analysis is to adopt the interdisciplinary field of LA and psychometrics. Exploring

the techniques in those interdisciplinary fields offers the possibility to advance how cohesion is measured. They enable the assessment of cohesion using digital trace data as students engage with online learning platforms.

LA presents a complementary research strand to contemporary research on group cohesion. For example, utilising methods of social network analysis as a commonly applied approach in LA research to understand how students communicate with each other (Dawson et al., 2014). Researchers tend to examine interactions occurring in learning networks, the density of cohesion, and emerging roles learners obtain in the learning process or understand the importance of social positioning for predicting learning outcome (Dowell et al., 2015; Gašević et al., 2013). Methods of automated content analysis are frequently applied to obtain timely and comprehensive insights into the topics being discussed in groups (Altebarmakian & Alterman, 2019a; Castro-Hernandez et al., 2015; Heo et al., 2010; Reffay & Chanier, 2003; Zheng, 2017a). While a consolidated and theory-informed model for studying group cohesion on either task or social aspects that would identify dimensions necessary for informing research and practice is lacking in the learning analytics research field (Zamecnik et al., 2022c), the study is exploratory and empirical. It aims to contribute to the development of such a model.

Research aims three

Developing important skills for learners, such as collaborating in teams, is paramount for solving complex problems (Lamb et al., 2017). One of the most prominent attributes a team needs to succeed with exceptional performance is the maintenance of team cohesion (Beal et al., 2003; Grossman et al., 2021; Kozlowski et al., 1999). In collaborative learning, cohesion fosters trust, leadership, satisfaction, communication and engagement that promotes learning (Garcia & Privado, 2020; Hansen, 2016; Tseng & Yeh, 2013; Xie et al., 2019; Yilmaz et al., 2020). The maintenance and continual support of cohesion are crucial for the teams learning. However, research that explores how cohesion changes in TML that focuses on the interplay between the team's cohesion and their learning constructs is scarce. The

alignment of cohesive perceptions in teams and how that cohesion evolves and impacts their learning. The absence of insights significantly reduces the capability of researchers and instructors to provide pedagogical interventions to support or improve cohesion and performance in small groups (Zamecnik et al., 2022c).

Current research in collaborative learning often positions team cohesion as an outgrowth, where other learning observations are often prioritised (Zamecnik et al., 2022c). The focus on learning processes predominantly drives the scope of studies in collaborative learning, technologies and methods to inform research and practice (Cress et al., 2021; Lämsä et al., 2021). In collaborative learning, studies that focus on characterising a group or team cohesion using trace data remain scarce. For instance, Altebarmakian and Alterman (2019a) have modelled team cohesion as the extent of thoughtful and meaningful collaborative interactions consisting of peer-to-peer feedback captured by an online learning platform. While such studies have produced novel insights drawing upon cohesion and collaborative learning constructs, research still lacks methodological approaches. As such, soliciting longitudinal constructs to understand how cohesion evolves in small groups and how instructors can use behavioural changes to support team cohesion (Zamecnik et al., 2022c).

One approach is to draw upon the growing interdisciplinary field of collaborative learning analytics (CLA) as a model for learners and their contexts using computational methods and psychometrics. CLA presents a mutually beneficial strand to contemporary research on team cohesion. It allows theory-informed educational or teamwork constructs to generate actionable group insights manifesting as feedback loops for instructors and teams (Martinez-Maldonado et al., 2021). They can help verify or frame theories in team cohesion to steer learners and improve their teamwork (Martinez-Maldonado et al., 2021; Wise et al., 2021). In doing so, automated data is captured from multiple salient data sources, analysed, and presented so that it is interpretable to inform instructors to improve collaboration and team learning. However, studies that have applied CLA to conjoin mental processes that teams externalise through their learning engagement and behaviour for cohesion remain to be explored.

Research aims four

Collaboration is a critical skill necessary for successful learning, work, and life (Lamb et al., 2017). Contemporary collaborative learning pedagogies are crucial for facilitating environments that help students hone these skill sets (Johnson et al., 2009). The pedagogical concept of collaborative learning is structured upon the notion that people learn from each other by working together, which helps build knowledge and teamwork skills that empower a more educated and engaged workforce (Dillenbourg, 1999; Laal & Ghodsi, 2012). As a result, educational providers are increasingly adopting collaborative paradigms to help prepare students for the challenges of the modern working environment where innovative and competitive teams are paramount to success (Gallagher, 2021; Verhoef et al., 2021).

A typical collaborative learning setting requires students to form teams to manage their tasks as they engage in collaborative work (Care et al., 2018). However, it becomes overwhelming if teams are not organised to manage and keep track of those tasks (Chang & Brickman, 2018). Maintaining productive collaboration is cognitively draining, as these environments draw on high levels of intrinsic and extraneous cognitive load (Kirschner et al., 2009). As such, high levels of cognitive load can disorganise a team, which leads to a higher risk of forming dysfunctional teams, creating issues in commitment (social loafing) (Latané et al., 1979) and motivation (free-rider effect) (Kerr & Bruun, 1983), eventually leading to diminished benefits of collaboration (Johnson & Johnson, 1991).

Different visualisation tools were developed to help increase reflection and group awareness to aid teams with their collaboration (Jermann & Dillenbourg, 2008). While visualisation tools enable awareness and reflection in teams, current research lacks support in understanding how these tools benefit collaboration (Liu & Nesbit, 2020). Many awareness tools in CSCL are not informed by instructional design and learning theory that allows for teams to easily digest and interact with visualisations for a more immersive experience that favours their learning (Liu & Nesbit, 2020; Martinez-Maldonado et al., 2015a; Matcha et al., 2020; Valle

et al., 2021). In this regard, the recent developments within the LA field, especially the inception of student-facing LADs, is empowering students to monitor and reflect on their learning through feedback informed by learning theories (i.e. self-regulated learning) that has a profound effect on learning (Jivet et al., 2021; Verbert et al., 2020). The importance of capturing how students utilise LADs and for what purpose, based on their roles, will allow opportunities to personalise their learning and increase the effectiveness of the dashboard (Bodily & Verbert, 2017; Roberts et al., 2017). As a result, researchers and educators will have the capacity to design a visual tool that provides learning value for teams by making their data visible, understandable and actionable which helps to optimise their learning (Martinez-Maldonado et al., 2015a).

1.2 Contribution

The theoretical contributions of this thesis can be classified into four categories, each corresponding to a research aim:

- Examined the state of the literature on team cohesion, identifying key trends, gaps and alignments with existing studies that corroborate findings.
- Employed an analytics-based measure to examine the temporal development of task cohesion based on theories of group synchrony that proximate cohesion.
- Explored how the cohesive perceptions of team members in agreement and disagreement evolve over time, including how these perceptions are characterised by their learning engagement, performance and feedback.
- Enabled the development of a new framework to understand how teams monitor and regulate their collaborative learning, based on the analysis of data obtained through the LA dashboard, leading to the development of new theories or concepts.

The practical contributions of this thesis can be classified into four categories, each corresponding to a research aim:

- Provided a comprehensive overview of the current state of research and the guideline foundations for future research.
- Provided an analytics-based measure for educators to support teams in technology-mediated learning that examines their cohesion as a proxy through learner trace data.
- Enabled the development of a targeted intervention to improve team cohesion and performance in real-world collaborative settings. As such, allowing the use of this knowledge to implement specific strategies that enhance team members' perceptions of cohesion, leading to better learning outcomes and performance.
- Developed a LA dashboard to help understand how teams monitor and regulate their collaborative learning, which can be integrated with learning platforms in collaborative settings.

Figure 1.2 provides a graphical summary of the content presented in this thesis. It highlights the problem, approach, and impact of each research aim.

The primary motivation for examining team cohesion in TML environments is driven by the need to provide students with learning experiences that support them in acquiring the skills in demand in their professional future. Examining cohesion in online learning environments will also help support teams with learning outcomes.

There has been a growing adoption of online learning tools, with a significant focus on providing students with flexible learning options (Stone, 2019). Such flexibility is important for non-traditional learners who do not follow the typical pathway of university students, often choosing to study later in life (Stone, 2019). A growing interest in upskilling drives non-traditional learners to develop their careers and seek promotions or a better work/life balance (Zamecnik et al., 2022b). These

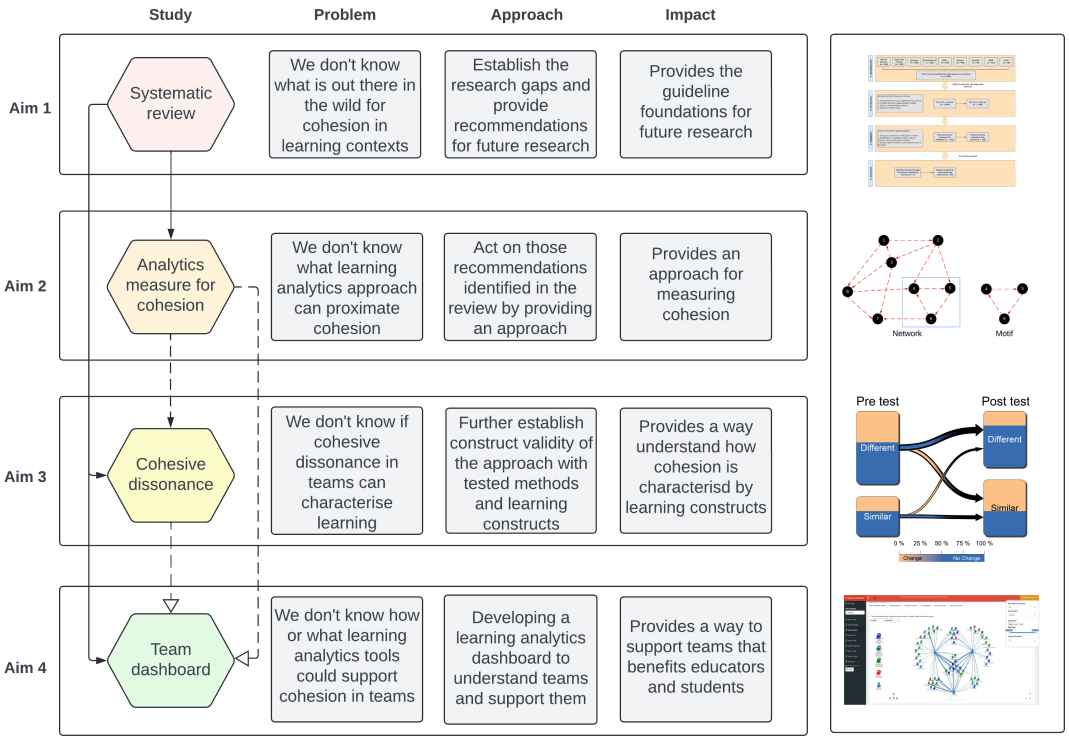


FIGURE 1.2: A graphical summary of the four research aims, common problems associated with them, the proposed approaches and impact

interests have only intensified in enrolment for online learning due to the COVID-19 global pandemic, which prompted governments to undertake social restrictions to alleviate the health system.

One significant consequence of the change to online learning is that it forced learners who wanted to study face-to-face into online learning environments or delayed their learning until the pandemic or government restrictions subsided (Shah et al., 2020). Learners who chose online study may find working with others problematic, especially in group projects, as there is an absence of social cues to help forecasts behaviours, a lack of peer or instructor feedback, and the potential of social loafing issues in the group (Gonzales et al., 2010; Kreijns et al., 2003; Shin & Song, 2011). Therefore, teams may feel more disconnected in those environments than in face-to-face settings. These consequences can severely impact team cohesion in online learning and their learning performance.

Measuring the temporal emergence of cohesion in teams and providing support

interventions can be one way to help alleviate pressures associated with online learning. The study of team cohesion presents an opportunity to discover what key learning constructs, such as peer or instructor feedback, interaction with learning resources and support mechanisms, can aid cohesion. In that sense, by knowing what factors contribute to nurturing cohesion, instructors can build on these discoveries and play an essential role in fostering cohesion in learning contexts. The enabling of cohesion will help teams to build skills that professionals need in today's knowledge work context.

1.3 Implications for research and practice

The practical implications of this thesis will help provide insights for researchers and educators to support team cohesion in TML environments from a theoretical and practical perspective. The thesis provides the trends of the current state of the literature regarding the measurement and analysis of team cohesion using trace data in TML. They will be able to reflect on the gaps and take the following steps by drawing upon the findings and recommendations to enhance team cohesion research in collaborative learning. The analytics-based measure of team cohesion offers a means to measure and analyse team synchrony emerging as students interact with their learning resources over time. These interactions are captured through the analytics-based measure characterising the temporal development of team cohesion. The approach provides the means for instructors to understand how well teams are likely to perform. However, it may not be appropriate for all types of learning environments to use. Characterising cohesive team perceptions through learning constructs, such as engagement, performance, team synchrony and feedback, will allow instructors to identify at-risk teams. Although, developing interventions that effectively address cohesion issues in teams need to be considered.

Lastly, the learning analytics dashboard (LAD) and how teams interact with it provide valuable insights into how team members and leaders monitor and regulate their learning. The dashboard helps reduce cognitive load and promote team collaborative learning and engagement. There are abundant opportunities to embed AI with dashboards for future research and development. Still, it is important to consider the ethical implications of using AI and LA in TML, such as biases in the algorithms used. Although not directly measuring or analysing cohesion, the study has meaningful implications for it. The dashboard developed in this thesis can incorporate the findings from the theoretical perspectives, analytics-based measures and how learning constructs align with cohesive perceptions to support cohesion monitoring by students and educators. It provides promising results that the dashboard tool can play a critical role in enhancing team cohesion. In terms of future implications for the thesis research, studies could assess how students and teachers interpret cohesion proxies while the dashboard is used in practice to illustrate them.

1.4 Thesis structure

This thesis is organised into eight chapters. Chapter 2 examines the current research on group cohesion in TML environments. It includes exploring the conceptualisation of cohesion and the methodological approaches used to measure, analyse, characterise and support cohesion in collaborative learning. Chapter 3 provides the overarching methodological framework to address all relevant research aims and concludes with the ethics and procedures related to the studies mentioned in this thesis. Chapter 4 addresses the first research aim through a systematic literature review of how the group cohesion of small teams has been conceptualised in TML. Chapter 5 addresses the second research aim using an analytics-based measure of cohesion to analyse the synchrony of teams as a proxy when interacting with their learning materials. Chapter 6 addresses the third research aim by characterising the evolution of cohesive perceptions in teams with their learning engagement, performance, team synchrony and feedback. Chapter 7 addresses the

fourth research aim by exploring how teams interact with the LAD and how it supports their collaborative learning. Finally, Chapter 8 concludes the thesis with a summary of how each research aim is addressed and how the research can be used for future work.

Chapter 2

Literature Review

This chapter provides a literature review on team cohesion in TML environments. It covers the state of the art in team cohesion, its temporal measurement, and the connections with engagement, performance, and feedback. The literature also examines how LADs can support collaborative learning in teams and covers the consolidated model of LA that underpins this thesis methodology. The chapter concludes with a summary of the literature review.

2.1 Cohesion in technology-mediated learning

The literature in this section motivates the need to synthesise the research on the cohesion of small groups in TML environments for Chapter 4.

2.1.1 Team cohesion conceptualisations and dimensions

There are limitations in the literature that reviews the cohesion of small groups in TML environments. One of the main limitations is the conceptualisations, such as drawing upon relationships between the dimensions of cohesion (i.e., task and social) and connecting those observations with their learning. In the contemporary

literature that has covered group cohesion extensively, there are existing formulations and methodologies with clear definitions that can be similarly adopted to aid in conceptualisation. The concepts used in contemporary literature mentioned below are drawn to help code the systematic review in Chapter 4 to address this challenge.

The conceptualisation of group cohesion

Multiple studies in organisational literature such as sports, military, professional work and education have been conducted to analyse the cohesion of small groups (Salas et al., 2015). Decades of research in this space have conceptualised group cohesion differently, such as unidimensional, e.g. members' attraction to the group or resistance to leaving (Seashore, 1954); or multidimensional, e.g. the sum of forces acting on members to remain in a group (Festinger, 1950). Based on existing reviews, the typical findings show that group cohesion is conceptualised as multidimensional and, to a lesser extent, unidimensional (Cota et al., 1995; Salas et al., 2015). Conceptualisations of group cohesion are needed to understand the key concepts and dimensions involved. This unification allows potential cross-study comparisons to increase research conclusions and researchers' effectiveness to identify standard metrics to enhance them and be effectively measured (Salas et al., 2015). Researchers in this area seek effective conceptualisations and the resulting dimensions with the most significant relationships with performance.

Data sources of group cohesion

The primary data collection methods for group cohesion studies across the board are surveys, such as self-reported questionnaires. Surveys are flexible, cost-effective, and generalisable, allowing researchers to understand a given population's broad characteristics to ensure construct validity (Shaughnessy et al., 2000). Surveys provide practical means of understanding behaviours and attitudes by assessing group cohesion. Such surveys utilise different measures to evaluate specific dimensions of cohesion, such as their task or social aspects (Carron & Brawley, 2012;

Carron et al., 1985). However, they hinder the participant from performing their work by forcing them to take time to answer questions. Furthermore, surveys are also challenging as they risk exposure to personal biases (Shaughnessy et al., 2000).

Unobtrusive methods have been recommended to address these issues as an alternative research methodology to study group cohesion (Altebarmakian & Alterman, 2019a; Salas et al., 2015). These methods include accessing log data or live records collected from digital devices and systems. For example, the collection of learning traces collected by LMS (Dobre, 2015; Schwendimann et al., 2016) or more recently, physiological behaviours and synchrony of eye gazing, body language, heart rate and brainwave data of members within a group (Gordon et al., 2020; Guo et al., 2019; Spikol et al., 2018; Yang et al., 2020). Similar studies can help gather a deeper understanding of how physiological components can impact group cohesion. However, Salas et al. (2015) argue that valid unobtrusive cohesion indicators must use theoretical underpinnings in assessment science to promote generalisation. This approach would ensure that studies can be repeated using the same process to gain further insights and advance research. Therefore a similar approach is adopted for the systematic literature review in Chapter 4.

Dimensions of cohesion

In the review of team cohesion measures by Salas et al.(2015), the authors identified the five most common dimensions of group cohesion and performance-related studies, namely (1) task cohesion, (2) social cohesion, (3) belongingness, (4) group pride and (5) morale. Task cohesion is commonly defined as the pull that keeps members together through a shared obligation to realise their ambitions and targets (Carron et al., 1985). Enhanced task cohesion levels are essential to a group's performance in reaching their objectives, such as being receptive to feedback and working towards a common strategy to achieve a goal. Social cohesion refers to the level of connectedness between group members based on their social interactions within a given environment (Carron et al., 1985). As shown by past research,

higher levels of social interactions can increase and maintain positive relationships within the group. Belongingness represents the degree of group members' sense of position (Shaw, 1981). This vital dimension is crucial for human emotional needs, such as feeling accepted and included in a group. Group pride is the level of fondness that the group exhibits, such as the importance of being a member (Beal et al., 2003). Lastly, the Morale dimension represents the level of devotion and endurance of each group member to remain within the group (Cartwright & Zander, 1960). Loyalty is crucial as it stands for commitment and trust. As a result, it allows group members to trust each other and be willing to take risks to achieve greater rewards. This review explores how these dimensions are considered by researchers studying group cohesion of small groups in collaborative learning platforms.

Measures and analysis of cohesion

To analyse group cohesion dimensions, researchers often measure cohesion at the individual, team or mixed level (Salas et al., 2015) using self-reported instruments, such as questionnaires. For instance, surveys are often used to capture an individual reflecting on themselves in the group or reflecting on their team members (Salas et al., 2015). Regarding the level of analysis, inferential statistical approaches driven by theoretical group cohesion metrics are used to analyse cohesion by calculating the average across all participants (individual) or aggregating each group and then calculating the average across those groups (team). This procedure allows for a practical synthesis towards understanding how researchers measure and analyse group cohesion (Salas et al., 2015). Specifically, an important focus of measurement identifies and analyse members' attitudes and behaviours within a group. Attitudes can relate to the sentiment of a member and their self-reflection or view of their group (Galyon et al., 2016). The behaviours can involve participating within the group socialising and outside professional environments (Chen & You, 2019; Gupta & Bakker, 2020).

2.1.2 Team cohesion in education

Previous systematic reviews in technology-mediated collaborative learning have mainly reviewed the social cohesion aspects in small groups. For instance, Kreijns et al. (2003) undertook a review to explain the potential pitfalls of social interactions in technology-mediated collaborative learning, cautioning that technologies enabling communication are not necessarily an incentive for interaction between group members. Goodyear et al. (2014) examine literature assessing diverse group processes emerging from various synchronous and asynchronous interactions in fully face-to-face and blended face-to-face and remote settings. Similarly, reviews by Dado and Bodemer (2017) and Jahnq (2012) show the limitations of the existing research that relies on social network analysis methodologies in studying the cohesion of groups in computer-supported collaborative learning. Another noteworthy review involved a meta-synthesis undertaken by Cherney et al. (2018), which examined literature concerning the small group interaction processes of collaboration in online learning environments, finding interdisciplinary issues across studies such as concepts and methodological approaches.

The literature concerning large groups or communities for the measurement and analysis of cohesion in online learning communities has been examined through the community of inquiry (CoI) framework (Garrison & Arbaugh, 2007; Jan et al., 2019; Kreijns et al., 2014). Learners in large online communities are typically defined differently than small groups in that they involve a community as a whole within a course without restriction to group size. Although studies involving learning communities of small groups through the CoI framework exist, they are limited in number (Cherney et al., 2018). The distinguishment between small and large learning communities is essential. Research shows that small groups are likely to have increased accountability, interrelationships, flexibility, contributions and dialogue than larger groups (Fay et al., 2000; Levine & Moreland, 1990). For instance, small groups have no less than two members and can range up to ten or more members, while communities can involve hundreds. While choosing the optimal number of members is situationally dependent, it is necessary to consider

that larger groups are more complex (Levine & Moreland, 1990; Wheelan, 2009). Therefore, managing the size of groups is crucial and can avoid further issues of counterproductive behaviours such as parasitism, social loafing or misuse of resources (Aubé et al., 2011).

The social interactions that infer cohesion in small and large groups have been studied across various educational settings. However, with the focus on small groups, existing research is not conclusive on how group cohesion can be defined in technology-mediated contexts drawing from learner trace data. For instance, exploring how cohesion can be analysed and measured from the learning interaction of teams. It is unclear what the standard approaches are and how they can support teams in TML. Finally, there is a lack of consensus on how group cohesion emerges and the association between various levels of group cohesion and collaborative learning outcomes in teams.

The systematic review in Chapter 4 is grounded and motivated by the approaches from the contemporary sciences that have defined, conceptualised, collected and analysed the dimensions of cohesion based on Salas et al. (2015) review. The systematic review closely adopts similar questions with a research focus on collaborative learning through technology-mediated environments of small groups. Similar frameworks are adopted to understand the definitions, methodological approaches and factors that impact and facilitate group cohesion in these environments.

2.2 Temporal measures of cohesion

2.2.1 Temporality of cohesion

Cohesion is one of the most researched topics in the literature concerning teams in management, healthcare, military, sports and other stress-induced environments regarding the relationships between the team and group performance (Beal et al., 2003; Kozlowski & Chao, 2012; LePine et al., 2008; Mullen & Copper, 1994; Santoro et al., 2015). Cohesion is a temporal construct that develops or emerges over

time and is known as an "emergent state" (Kozlowski & Klein, 2000). Kozlowski and Klein define the emergent state as "a phenomena that originates in the cognition, affect, behaviours, or other characteristics of individuals, is amplified by their interactions and manifests as a higher-level collective phenomenon" (Kozlowski & Klein, 2000, p. 55). For example, team members with similar values begin to develop common grounds between individuals, such as their attitudes and beliefs regarding the team's cohesiveness (Santoro et al., 2015). As the team starts to form, these perceptions are challenged by events that may impact the common grounds of the team. Eventually, the ideas and views converge, and the team reaches a shared state of team cohesion (Santoro et al., 2015, p. 118-119). Further characteristics include the process mechanisms of a team, such as the patterns that take shape (i.e. dyadic and triadic interactions that cycle or oscillate) and the temporal nature of the whole process (Marks et al., 2001; Santoro et al., 2015). Conceptualising cohesion in such a manner is of utmost importance when measuring cohesion as a process.

According to Tan and colleagues 2021, educational platforms designed for complex problem-solving aim to foster the development of team skills that are crucial for students' future professional careers. However, the extent to which these platforms effectively promote and measure team skills acquisition is still a matter of debate and requires further investigation. Nevertheless, Team skills include accountability, relationship building and shared commitment to achieving the team's goals. With these team skills, cohesion becomes a critical factor in creating and strengthening the bonds of the team to ensure high academic performance leading to success. Measuring team cohesion in educational platforms designed for complex problem-solving is a challenging task for several reasons. These platforms often involve large numbers of participants, sometimes in the thousands, which can make it difficult to collect and analyze data on team interactions and dynamics (Sluis et al., 2017). Additionally, relying on self-reported questionnaires to measure cohesion requires motivating individuals to complete them accurately, which can be challenging when students are already busy with coursework and other responsibilities (Wright, 2005). Finally, attrition rates in online courses can

be high, making it difficult to obtain data on the entire team throughout the duration of the course (George et al., 2019). Further research is needed to develop effective methods for measuring and promoting team cohesion in educational platforms for complex problem-solving. Educational instructors cannot know how cohesion changes over time in team learning without the intrusive methods of surveys. Instructors cannot intervene, investigate and single out the potential causes of team issues based on observation (i.e., team member behavioural interactions with learning content) that change over time. Therefore, approaches that utilise learners' digital footprints, such as process data from technological infrastructure, provide the opportunity to develop temporal-based methodologies and build a greater sense of the complexity in teams, such as their learning and cohesion processes (Klonek et al., 2020; Lazer et al., 2009; Luciano et al., 2017).

Educational researchers have utilised trace data collected by learning management systems to measure the complexity of human behaviours, learners and pedagogical support outcomes with analytical tools from quantitative and qualitative data (Ifenthaler et al., 2020; Slater et al., 2016). Recent studies show advances in utilising trace data to measure group cohesion using behavioural engagement measures for task cohesion, such as the degree to which students cognitively engage with their work and group (Altebarmakian & Alterman, 2019a). Task cohesion is a key aspect of group performance that emphasises completing goals with a collective task focus (Zaccaro et al., 1995). To achieve task cohesion, the team needs to actively interact and work towards their goal together, which requires engagement. Using behavioural engagement measures as indicators of task cohesion in learning management systems is promising. Task cohesion is shown to be positively related to the engagement of team learning behaviours (den Bossche et al., 2006). In contemporary literature, researchers have a growing consensus that the nuances of engagement in teams, such as their commitment towards a goal (Marks et al., 2001), are impacted by factors such as cohesion (Forsyth, 2021; Waight & Edwards, 2021). Behavioural interactions characterise task cohesion as evidence of commitment, unity and resolve to complete a task (Carron et al., 1985).

Therefore, engagement is a key component of achieving task cohesion. There are further calls to consider the temporality of team processes, such as engagement, as an indicator of cohesion using temporal data without relying on survey data (Kozlowski & Chao, 2018; Santoro et al., 2015). Despite the promising potential of using behavioural engagement measures as indicators of task cohesion in learning management systems, the task aspects of prior research related to studying cohesion using trace data are limited (Zamecnik et al., 2022c). This limitation challenges replicating or extending studies and highlights the need for more research to understand how cohesion develops over time in similar environments. As such, innovation concerning design or approaches is needed to address the gaps in technology-mediated learning literature. One approach to help define the measure and analysis of cohesion in a learning context is to draw upon similar studies in other domains.

2.2.2 Synchrony as a key component of group cohesion

The research of group synchrony is becoming prominent across multiple disciplines. Recent studies show that behaviours related to synchrony are predictors of cohesion and performance (Dindar et al., 2020; Gordon et al., 2020; Mayo et al., 2021; Swol & Kane, 2019). Synchrony develops within groups that exhibit patterns aligned on the same spectrum, such as how birds of the same feather flock together (Reynolds, 1987) or how people bond through social interactions (Cross et al., 2019; Wiltermuth & Heath, 2009). These behaviours often include spontaneous cyclic or rhythmic temporal interactions between individuals that occur naturally.

Group synchrony is essential for developing group cohesion (Kerr & Bruun, 1983; Latané et al., 1979). Synchrony in groups allows teams to develop patterns of behaviours so they can coordinate, cooperate, and perform their tasks effectively (Gordon et al., 2020; Jackson et al., 2018; Mayo et al., 2021; Wiltermuth & Heath, 2009). Synchrony of interactions occurs in teams, where they exhibit

workflow patterns, such as working together to execute a process. Such workflow patterns act as cycles or rhythms to coordinate and complete tasks and goals as a team (Tesluk et al., 1997). A meta-analysis by Beal et al. (2003) regarding cohesion-performance relationships found that as team workflow patterns increase, the relationship between cohesion and performance becomes stronger. As a result, the intensity of workflow becomes a strong indicator of cohesion (Beal et al., 2003; Forsyth, 2021; Marks et al., 2001; Tesluk et al., 1997). Interestingly, a study by de Jong et al. (2014) suggests that when team members have negative relationships that impact cohesion, higher team-member exchanges and task independence help mitigate the adverse effects and improve cohesion. Nevertheless, decades of literature on team processes, workflows, and synchrony interactions have been shown to predict improved cohesion and performance (Beal et al., 2003; Chang & Bordia, 2001; Mullen & Copper, 1994; Salas et al., 2015). This thesis uses a similar approach, examining records of WIL team interactions as measures for team cohesion.

The synchrony of groups in face-to-face learning environments is mainly investigated through physiological components, such as brain activity, heartbeat, facial expressions, body posture and movement (Bevilacqua et al., 2019; Chikersal et al., 2017; Dindar et al., 2020; Schneider et al., 2020). Researchers are typically interested in many behaviours, such as how individuals interact with their peers and teachers, learn, and problem-solve together. For example, understanding and discovering the behavioural nuances in cognition and socio-emotive exchanges of teams when learning and how it impacts educational outcomes. Currently, literature in education exploring psychological or interpersonal synchrony through log data collected from LMS is non-existent from current knowledge as of the time of writing. Although the data collected from these platforms rarely contain physiological data, they still provide evidence of synchrony, such as how a team interacts with learning resources (task aspects) and socially engages in groups or teams (social aspects), which are processes of workflow manifestations between individuals in learning (Gasevic et al., 2017; Joksimović et al., 2019). Therefore, group synchrony based on member interactions can be understood for cohesion,

such as how they strategise their learning and utilise learning resources to succeed. However, challenges remain to illustrate and interpret the synchrony structures of the team learning phenomenon, such as the dynamic growth of team interactions with their learning materials over time.

2.2.3 Analysing group synchrony through network science

The contemporary literature related to the measurement and analysis of team cohesion is driven by the need to focus on unobtrusive methodologies, such as data science approaches that analyse a continuous stream of data from team interactions (Kozlowski & Chao, 2012, 2018). In this regard, contemporary literature shows the potential of network science to deepen the understanding of group synchrony through analysis of temporal behavioural interactions (Mohammed et al., 2021; Santoro et al., 2015). Network science allows for the study of complex structures or processes of change in a natural phenomenon by representing relationships (i.e. edges) between variables of interest (i.e. nodes) illustrated by graphs to show interconnections between a set of entities (Wasserman & Faust, 1994). In our context of studying group cohesion, the nodes represent individual team members, while the edges represent the synchrony of interactions with different learning resources.

One particular form of network analysis important for understanding group cohesion is the analysis of temporal network motifs (Paranjape et al., 2017). Generally, network motifs are subgraphs of a more extensive network (see 2.1) with statistically significant repeating structures that characterise a network's composition (Milo et al., 2002, p. 825). They help understand the deep functional properties of networks defined by a particular pattern to explain a complex phenomenon, such as the patterns of collaborative behaviours between people (Chakraborty et al., 2015; Jurgens & Lu, 2012). There is potential for motifs to be used in the same sense for understanding group synchrony.

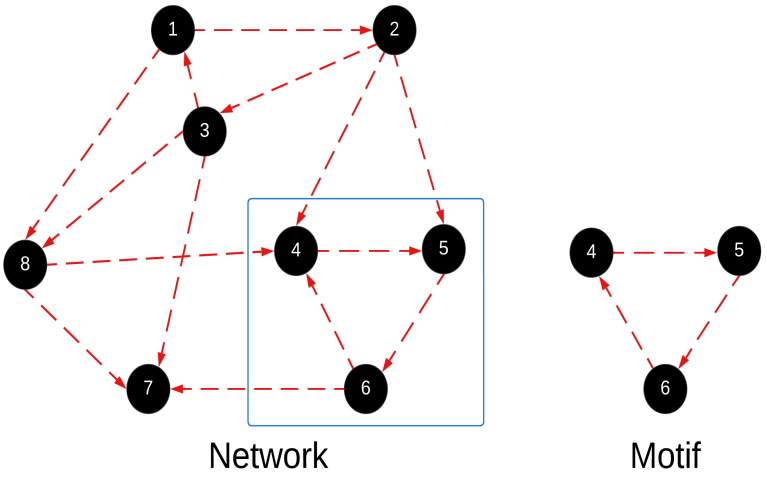


FIGURE 2.1: Example of a network (global structure) and the associated motif (local structure)

An important area of application of temporal network motifs in the learning domain is understanding group cohesion by looking at the synchrony of the team's engagement with an LMS platform (Santoro et al., 2015). Here, group synchrony is used as a proxy for cohesion, given the critical role of synchrony in establishing group cohesion. Such an approach offers a reasonable alternative to obtrusive and labour-intensive methods such as self-reports (Kozlowski & Chao, 2018). Santoro and colleagues (2015) suggest that networks showing the interactive behaviours between team members can be one approach to help explain the dimensions of cohesion. These claims are further supported by Forsyth (2021) that cohesion can be intuited from direct observation of the group's behaviour. For instance, high levels of engagement and behavioural synchrony may serve as indirect indicators of cohesion (Swol & Kane, 2019). Our analysis employs temporal network motifs to precisely approximate task cohesion behaviours based on team interactions with their learning resources. Given that cohesion is an emergent state that develops over time, representing the synchrony of different forms of cyclical, reciprocal or repetitive behavioural interactions, using temporal network motifs may help approximate the level of task cohesion through the synchrony of behavioural interactions.

In our approach, we pay special attention to the alignment of theoretical, contextual, methodological and practical factors regarding the construction of student interaction networks, given their important for drawing meaningful interpretations (Chen et al., 2022a). The theoretical background mentioned in this study indicates that active behavioural interactions closely represent group synchrony. Given that group synchrony is a strong predictor of cohesion, we postulate that the analysis of temporal motifs can approximate the temporality of task cohesion in teams depending on how they engage with their learning activities. These interactions over time can be captured in a WIL learning platform. Therefore, applying temporal motifs as a measure for group synchrony and cohesion analysis is warranted. The practical implications of applying temporal network motifs can aid instructors in understanding the extent of task cohesion present in teams based on the shapes, frequency and growth of interactions with their learning resources.

Grounded and motivated by the promising use of motifs across multiple disciplines and their applications to understand the synchrony of complex systems, we postulate that different shapes of motifs, such as the way team members interact with learning resources and how long they take to manifest, can exhibit the nature of cohesion in teams through the way they interact with learning resources.

2.3 Characterising learning constructs with respect to cohesion

2.3.1 Team cohesion and collaborative learning

Team cohesion has been extensively researched in the contemporary literature that focuses on the relationships between team effectiveness and performance (Beal et al., 2003; Kozlowski & Chao, 2012; Salas et al., 2015). One of the main dimensions of team cohesion showing to consistently predict and have a positive effect on performance is task cohesion (Dimas et al., 2021; Grossman et al., 2021; Salas et al., 2015; Zaccaro et al., 1995; Zamecnik et al., 2022c). Early works by Zaccaro (1991)

regarded cohesion as a multidimensional construct consisting of task cohesion and social cohesion as its dimensions. An important dimension – task cohesion – emphasises completing goals that are a collective task focus, which is the contributions of more than one individual and requires accomplishment given by a set timeframe (Zaccaro et al., 1995). A highly task cohesive team will persist in facing stresses and obstacles (Zaccaro et al., 1995). Behavioural interactions characterise task cohesion as evidence of commitment, unity, resolve and will to complete a task (Carron et al., 1985). In other words, members that are task cohesive are not because of their friendship bonds but their common goals to work together as a single group through coordinated group effort (MacCoun et al., 2006). Research shows the support that the intensity of workflow becomes a strong indicator of cohesion (Marks et al., 2001; Tesluk et al., 1997). Teams with negative relationships with the mediation of higher exchanges and task independence help to mitigate negative aspects of team performance and improve cohesion (Jong et al., 2014).

Several studies have conceptualised task cohesion in collaborative learning through technology-mediated environments according to the contemporary literature in organisational sciences (Zamecnik et al., 2022c). Researchers studied the relationships between the team's task cohesion and the effects of learning constructs using survey methods. For instance, they examine how teams self-regulate when they learn and consider valuing the task (Bilgin & Gul, 2020; Zheng, 2017b). Moreover, some explored the relationship between the task cohesion of teams in a gamified collaborative learning environment and how it aids their performance (Terzidou et al., 2016). These learning constructs have all positively impacted the team's task cohesion in collaborative environments. Studies have demonstrated that task cohesion is also a reliable predictor of performance in blended and online collaborative environments (Wang & Hong, 2018; Wang & Hwang, 2012; Williams et al., 2006). The existing studies reveal an aligned narrative with contemporary literature, where cohesive groups demonstrate greater productivity (Schachter et al., 1951), which aligns with the positive relationship between task cohesion and performance in learning. A significant study aimed at measuring team cohesion

using learner trace data involves quantifying the level of thoughtful and meaningful comments that students exchange with each other in an online collaborative environmentt (Altebarmakian & Alterman, 2019a). Such studies are helpful as they can offer an alternative to measuring cohesion using surveys and allow instructors to act on data insights to improve the team's cohesion over time and place. While such insights are of value, more research is required to explore and understand how other components of learner trace data, such as their learning engagement and feedback over time, can help further characterise task cohesion.

2.3.2 Team feedback

Feedback is crucial for team learning and performance, as it is a lever used to regulate the team's processes and emergent states, such as their cohesion (Gabelica et al., 2012; Kozlowski & Ilgen, 2006). Gabelica (Gabelica et al., 2012) reviewed the types of feedback that are important for teams to perform in higher education, namely, performance and process feedback. Performance feedback is conceptualised as "the provision of information about individual or group performance to reinforce good performance or to correct poor performance enabling improves to be made" and process feedback as "information regarding the way one performed a task and reached expected results" (Gabelica et al., 2012, p.125). For instance, the former can describe specific feedback related to the task, whereas the latter focuses on behaviours, actions and strategies. Feedback at the team level is more effective as it enhances the team's efforts toward collective goals instead of individual goals when feedback is provided at the individual level (Handke et al., 2022). Feedback is instrumental to improving the team's performance and regulation when initiated early and reflected upon.

Although feedback provided to teams is an important feature of collaborative experiences, its connection with team cohesion has not been adequately explored (Zamecnik et al., 2022c). The type of feedback and delivery is also important for its effectiveness Hattie and Timperley, 2007. As such, Hattie & Timperley Hattie and Timperley, 2007 created a feedback model that identifies the circumstances that

make it effective with questions that relate to feeding up (i.e., future direction), feeding back (i.e., current direction) and feeding forward (i.e., next direction). These questions can be further broken down into four feedback levels, namely, task level (FT), process level (FP), self-regulation level (FR) and self-level (S). FT is related to the assessment of a task performed, FP is related to the strategies, actions and behaviours required to perform the task, FR is related to the self-monitoring directing regulation of actions, and S is related to personal evaluations or appraisal of the learner or group (Hattie & Timperley, 2007).

Many studies have applied this feedback model in learning analytics to draw upon relationships between the four feedback levels with various factors that impact learning and practice. For instance, in the individual learning context, Pinheiro et al. (2019) and Osakwe's (2022) incorporated textual features (i.e., affective processes, social processes and pronouns) and sentiment to characterise the four feedback levels. In the collaborative learning context, Harney et al.(Harney et al., 2015) study explored task-level and process-level prompts on a team's argumentation style, consensus and perceived efficacy. Although, studies exploring the differences in how mentors and clients provide these prompts to teams in WIL remain to be seen.

The main goals of work-integrated learning are to provide learners with an opportunity to apply their academic knowledge into practice, build professional networks and employability (Campbell et al., 2021). As such, WIL allows learners to engage in work placements, working on real-world projects with an industry partner to develop their professional competencies (Ferns et al., 2015). For learners to attain new desirable skills and abilities, quality feedback provided by mentors and clients is crucial (Cooper et al., 2010a; Peach et al., 2014) and communication between mentor and client is key for consistent feedback to avoid confusion by the learner. Therefore, feedback plays a critical role in the success of the team.

While feedback labels have not been extensively explored in WIL or collaborative learning contexts, there are benefits to adopting learning analytics to support research and practice in these environments (Gasevic et al., 2019; Wise, 2019).

For example, opportunities that improve the quality of provisional feedback, such as backward evaluation, allow teams and their supervisors to reciprocally reflect and evaluate the feedback (Misiejuk & Wasson, 2021). Backward evaluation is defined as 'the feedback that an author provides to a reviewer about the quality of the review' (Luxton-Reilly, 2009, p. 226). The approach will help refine the way feedback is provided and enhance the future performance of learners when the delivery and quality of the feedback are improved. To improve feedback, it is important to investigate team feedback perceptions (Misiejuk & Wasson, 2021). As such, investigating how teams perceive the helpfulness of feedback from their supervisors and what feedback these supervisors provide to their team (i.e., that targets the task, process, regulatory and self-level). These approaches can help improve the quality of feedback and experience for teams in WIL or collaborative environments.

2.3.3 Measurement and analysis of task cohesion

The analysis of task cohesion in collaborative learning contexts is mainly dominated by cross-sectional surveys (Zamecnik et al., 2022c). Traditionally, dimensions such as task cohesion originated from Carron and colleagues (1985) Group Environment Questionnaire (GEQ) in sports teams, which has since gradually adjusted over time to accommodate and be flexible for measuring the cohesion in work teams (Carless & Paola, 2000). Typical questions related to measuring task cohesion include the team's level of commitment, unitedness, receptiveness and shared responsibility to complete a task. In educational and organisational contexts, cohesion-based surveys are typically aggregated at the team level instead of the individual level, as they yield better cohesion-performance relationships (Salas et al., 2015; Zamecnik et al., 2022c). Studies examining inter-rater reliability (IRR) scores, such as the degree of agreement between team members to determine team cohesion and the evolution of their cohesive perceptions over time that is similar or different, are limited. The importance of cohesion measures in such ways provides the means for mitigating team issues that reduce motivation (Karau &

Williams, 1997). There may be hidden benefits towards further understanding the team's cohesion in teams by observing their behaviours over time while they study, such as how the dynamics of stress and conflict from team members impact performance.

2.4 Supporting teams with dashboards

2.4.1 Collaborative learning

Collaborative learning, defined in a simplified sense, involves a situation where two or more people construct knowledge together. Dillenbourg (1999) further argues that collaboration is a much deeper and more complex phenomenon, characterised by a situation, interaction, learning mechanism, and the potential outcomes of collaboration. Collaborative learning can occur in various educational contexts that aim to construct knowledge through synchronous interactions of small groups that involve many settings, such as computer-mediated learning with mobile and web-based learning technologies (Amara et al., 2016; Hron & Friedrich, 2003).

Collaborative learning promotes learning, and when intertwined with technology, it enhances collaboration (Chen et al., 2018; Jeong et al., 2019; Vogel et al., 2017). Since the inception of CSCL research in 1995, several meta-analysis reviews have provided unequivocal evidence for the importance of collaborative learning to support students' learning outcomes and enhance skills such as teamwork and problem-solving (Stahl & Hesse, 2006). According to King (2007), activities that promote collaborative learning include 'thinking out loud' or asking 'thought-provoking' questions where group members hear diverse viewpoints that develop their learning. Such activities can spark 'ideas' that members share with their group and expose them to 'criticism' and 'advice'. Listening to 'feedback' from their group allows members to fully understand a topic from all angles. These processes promote 'critical thinking' skills by taking feedback and adjusting their

'own viewpoint' as new ideas emerge. These socio-cognitive processes help members learn and retain new knowledge. Considering the emotional and motivational states in collaborative learning is also of great importance (Järvenoja et al., 2020), as team members need to monitor and control situations that may harm productive collaboration.

2.4.2 Supporting collaborative learning

Given the complex nature of collaborative learning environments, research suggests that students require additional support to promote collaboration (Rummel & Spada, 2005). One such tool in CSCL is visualisation tools, such as group awareness tools that enable productive learning (Bodemer, 2011). These awareness tools include mirrored-shared systems, participation and ambient displays that help monitor and regulate group learning through reflection (Liu & Nesbit, 2020). Successful groups must monitor and regulate their processes to succeed in collaborative learning (Hadwin et al., 2011). As such, students who utilise group awareness tools will observe the current state of their team (i.e., monitor) and determine if tasks are being addressed and contributed to by each member, depending on the context of the pedagogical environment. If issues are determined, teams need to control (i.e., regulate) and adjust their collaborative learning to reach the desired state that makes the team productive. However, group awareness tools have weaknesses, such as not capturing collaborative learning processes over time and are seldom used for students directly (Liu & Nesbit, 2020). One promising approach has been the rise of dashboards, given their interactive and dynamic nature in illustrating activities in real-time (Few, 2006). As a result, it has gathered increased interest in CSCL contexts for adaptation (Liu & Nesbit, 2020).

2.4.3 Learning analytics dashboards to support learning

Dashboards are visualisation tools that harness raw data from multiple sources, such as databases and spreadsheets, into a single interface to report on key indicators at a glance view (Few, 2006). In that sense, dashboards go beyond simple screen displays and provide illustrations based on consolidated data processes arranged on a single screen where information can be dynamically viewed (i.e. interaction with visualisations) (Few, 2006). For instance, learning analytics dashboards (LADs) provide insights into learning processes by aggregating different indicators into visualisations that aid in monitoring learning behaviours and outcomes over time (Schwendimann et al., 2017; Verbert et al., 2013). The inception of LADs was brought forth by the rise of data from LMS, allowing instructors to visualise and monitor student engagement and performance indicators (Macfadyen & Dawson, 2010). Two kinds of LADs in the educational context have emerged: teacher-facing and student-facing (Bodily & Verbert, 2017; Verbert et al., 2013). Examples of early designs for teacher-facing dashboards include early warning systems to inform instructors about students labelled as 'at-risk' (Aguilar et al., 2014) to help initiate timely interventions by providing pedagogical support for students falling behind. Student-facing dashboards include recent designs that empower students to personalise their learning. It allows learners to choose what indicators from a dashboard they would like to monitor and receive feedback during their learning (Jivet et al., 2021). Since the inception of LADs, there have been early issues of "one-size-fits-all" designs due to the lack of personalisation provided for students to benefit everyone's learning (Teasley, 2017). Nevertheless, research in LA increasingly shows that when students are informed by learning theories and instructional design, they provide opportunities for students when they are conveyed in a meaningful way that enhances learning (Jivet et al., 2021; Zamecnik et al., 2022a).

2.4.4 Collaborative learning analytics

LA is an area that shows promise in supporting and developing human agency and learning (Wise et al., 2021). In that sense, it is helping to increase our knowledge of collaborative learning and support by connecting fine-grained trace data and learning constructs. This novel research paradigm is known as collaborative learning analytics (Wise et al., 2021), which aims to support collaborative learning through LA approaches. The main role of LA is to expand on current collaborative learning information of learning processes that are captured and analysed in more actionable ways and insightful (Martinez-Maldonado et al., 2021). In the context of adaptable CSCL systems (i.e. dashboards and other visual tools), they can include analytics embedded as part of the interface used for collaboration to support reflection and awareness of learning processes through visual representation and feedback (Echeverria et al., 2019; Herder et al., 2018; Tan et al., 2017). These adaptable systems can help provide the community of CSCL a means for more grounded research, providing real-time analysis and scalable feedback to improve collaborative learning outcomes (Martinez-Maldonado et al., 2021). However, adaptive systems in collaborative learning, such as LADs, are scarce. Answers are lacking regarding how teams interact with dashboards and the consequential implications on their collaborative learning processes and perceptions.

Given the limitations in exploring LADs in CSCL contexts, several gaps remain to be considered. First, LADs designed for K-12 contexts need to be further explored to understand how tools enhance teams to regulate their learning in young adults. Second, developing the capability of tracking LADs usage that helps increase our understanding of how students engage with the tool and the connections that can be inferred to their learning behaviours using LA (i.e. collaborative learning contexts). Lastly, establishing perspectives of students in terms of how dashboards impact their collaborative learning and metacognitive activities. This thesis addresses all these issues.

2.5 Summary

This literature review provides an overview of the current state of cohesion research in TML environments. First, the differences between the educational and organisation context when it comes to conceptualisation, definition and measurement are covered. Second, the key definitions and measurements for the temporality of cohesion are reviewed, and the characterisation of synchrony as a component of group cohesion is explained. Third, the literature connecting studies with collaborative learning and team cohesion is explored, including the relationships between team feedback and how it motivates cohesion. Fourth, studies that have involved LA dashboards in supporting collaborative learning are covered. The definitions of collaborative LA and how it can support teams through dashboards are noted. The background from this chapter will help operationalise the studies in this thesis and motivate the research questions to address each research aim.

Chapter 3

Overarching Methodology

This chapter describes the overarching methodological framework to address the aims of this thesis. It covers the research paradigm, research design, data collection, data analysis, ethics, reflections and concludes with a summary.

3.1 Research paradigm

The consolidated learning analytics model is a comprehensive framework for studying and understanding how learners from trace data collected in TML environments can inform the study's design and analytical approach, such as data science, to bridge theory and practice (Gašević et al., 2017). Therefore, it is a suitable research paradigm to adopt and uncover the complexities of team cohesion and learning in collaborative TML environments. The model integrates different research perspectives, such as cognitive, social, and affective aspects of learner behaviours, to develop a more holistic approach to investigating their learning process and outcomes (Gašević et al., 2017). At its core, the model recognises that learning is a multifaceted and dynamic process influenced by various factors such as the learners' background, motivation, and interaction with the learning environment (Dawson et al., 2014). The adoption of this paradigm helps to develop a more nuanced understanding of behaviours in teams, such as their cohesion

and how teams can be supported through learning analytics (Gašević et al., 2017). The adoption of this research paradigm leads to a holistic and interdisciplinary approach to studying technology-mediated learning environments, which can lead to more nuanced and informative findings (Gašević et al., 2017). For instance, address the lack of links between the principles established in the discipline, on which LA builds as the woodwork field for educational technology research, psychology, human-computer interaction, learning sciences, data mining or research methods (Gašević et al., 2017). The consolidated model, as seen in Figure 3.1 below, addresses the lack of links between the principles established in the discipline. The illustration comprises three dimensions for LA: theory, design and data science to illustrate the crucial interrelations. This model is adopted to underpin the work throughout the thesis.

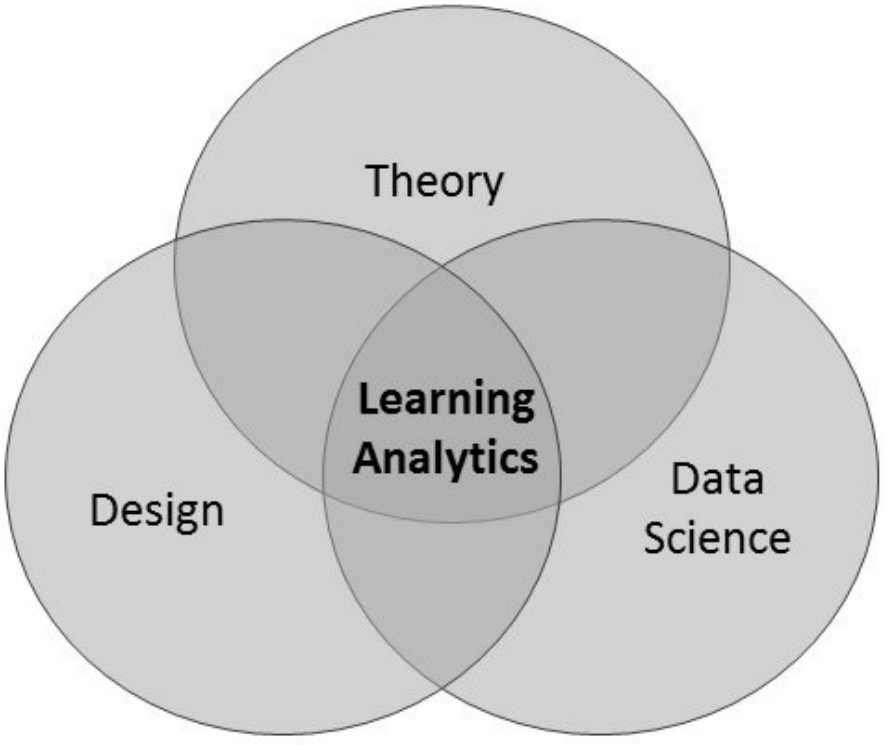


FIGURE 3.1: Consolidated model of learning analytics (Gašević et al., 2017)

3.2 Research design

The consolidated learning analytics model provides a suitable research paradigm for investigating team cohesion in TML. The model recognises that learning is a complex and dynamic process influenced by various factors, including the social and task aspects of learner behaviours, which are crucial to understanding how teams collaborate and work towards a common goal. In the context of research in the thesis, adopting these paradigms aligns with the research aims and subsequent research questions detailed in Chapter 1.

A comprehensive understanding of the related work regarding team cohesion analysis in TML was needed for the research aims to inform theory and practice in education. As such, the way definitions, conceptualisations, and measures of team cohesion, including how studies substantiate or influence cohesion, needed to be synthesised to provide a guideline and recommendations for future studies using learning analytics. A systematic literature review (SLR) is conducted to cover the breadth and depth of cohesion studies of small groups in TML environments that follow the PRISMA framework (Moher et al., 2009) for robust synthesis. The design led to further research opportunities to address the knowledge gaps identified in the SLR. As a result, an analytics-based measure was developed informed by the theoretical underpinnings in contemporary literature that comprehensively studied the dynamics of team cohesion (Salas et al., 2015; Santoro et al., 2015). Moreover, the approach is informed by LA and applied in a collaborative TML setting to directly contribute to using unobtrusive approaches for analysing team cohesion. Following the findings and implications of that contribution, quantitative and qualitative approaches were used to further ground the analytics-based measure, while investigating the connections between team cohesion perceptions and the alignment with their learning constructs, further contributing to the gaps outlined in the SLR. Finally, the LAD was developed based on the opportunity to study how teams interact with the LA tool and how it supports their learning. The dashboard allows for the compatibility of integrating the analytics-based measure of cohesion and examining how teams cohesion changes, along with their

perceptions, as a potential research avenue that demonstrates the power of the consolidated model of LA in producing contributions to the field of LA.

3.3 Data collection

The data collected throughout the thesis for each study are diverse and, in some cases, specific. Throughout the thesis, methods such as surveys, focus group interviews, and observational data collection approaches from learning systems that are obtrusive or unobtrusive were used to collect the data. Specifically, observational data was unobtrusively collected for the learning analytics-based measure contribution, providing minimal impact on the teams' learning as the data was archived throughout the studies in this thesis. Log trackers were developed and integrated into the dashboard that collected the user's interactions with the dashboard's features to collect real-time data on the team's engagement unobtrusively. Surveys were introduced to willing participants while actively learning in the TML environment. The focus group interviews collected video and audio transcripts of willing participants. The survey and focus group interviews were obtrusive. In the case of the SLR, it was unique as peer-reviewed articles were collected from multiple databases using a systematic literature review management tool called Covidence[1]. The data collected for the SLR was unobtrusive, as the collection impacted no participants or people.

3.4 Data analysis

The data analysis in this thesis uses various software and statistical techniques to analyse the data. Beginning with the software, the Covidence tool, as mentioned previously, is used to collate the articles collected from the databases based on the inclusion and exclusion criteria outlined in the methodology section of Chapter 4. The software can handle duplicate information and record the changes per article

[1] Covidence management tool

done by the users, reducing data quality issues. The tool provides a file output that helps researchers synthesise the information and extract key findings to inform on the SLR results, discussion, and knowledge gaps for research aim one. Another software called the SNAP library (Leskovec & Sosič, 2016) uses an algorithm to analyse and count the different temporal motifs. Although the algorithm in the software is pre-defined with a template, adjustments to the code were made to produce the data that is needed for further analysis to answer questions of how group synchrony can be used as a proxy to measure the task cohesion of teams for research aim two. The final software involves a LAD developed due to an opportunity to understand how teams interact with LADs using log trackers and how it can inform collaborative learning and regulation. Moreover, the dashboard was integrated with a TML platform called the Challenge[2] platform, which enabled the internal analysis of the data and provided visual feedback back to teams on their progress. To account for issues that may lead to uninformed visualisations, the LATUX framework (Martinez-Maldonado et al., 2015b) was incorporated to design the dashboard while considering continuous feedback from teachers and students.

The statistical techniques used varied based on each research aim in the thesis. Descriptive measures were used to derive means, percentages, and counts of learner behaviours, and interactions with learning content or dashboard features. These measures were presented in either table format or graphically, such as bar charts. They help explain the team's characteristics, such as how they engaged with other team members or with their learning content. To understand if these interactions or engagements were significant, including their performances, the testing of p values using Kruskal-Wallis (Kruskal & Wallis, 1952) and post hoc analysis of grouped or nested data with the Dunn-Test were used to test significant differences in engagement and performance data between teams. These specific techniques are used for non-parametric data typically used for engagement data, as the data is not distributed normally.

[2]Challenge platform

Data science techniques, such as K-means clustering, were used to cluster the engagement of teams interacting with their learning activities and help identify patterns that describe the learning strategies of teams for research aims two and three. To mitigate the issues of the random numbering of clusters, the Silhouette technique was used to approximate the optimal number of clusters, where each cluster is appropriately characterised. Summary statistics were used to help further analyse each cluster. Temporal network motifs were used to analyze group synchrony, which is closely related to coordination and collaborative interactions, to approximate team cohesion for research aims two and three (Paranjape et al., 2017). The number of counts of each motif was explored, which could range up to thousands. Normalisation was performed to provide a clear understanding of the distributions between each motif to handle the ranges. Epistemic network analysis (ENA) was used to examine how connections between how feedback is provided to teams with different perceptions were related in research aim three (Shaffer et al., 2009). The approach provides a way to understand these relationships visually. Feedback provided to each team by their industry supervisors was collected from the LMS and manually categorised by the four feedback levels based on Hattie & Timperley's model (2007) that includes feedback on the task, process, regulatory, and self. That way, the data could be used as input for ENA analysis.

Finally, a thematic analysis was identified as the most appropriate to help identify themes and patterns of the focus group data collected from the video and audio transcripts concerning their interactions with the LAD to address the research aim four. Steps for the thematic analysis included familiarisation with the data, generating initial codes, searching for themes, reviewing the themes and writing up the results from the text. The overall result explains how the LAD impacted team learning and their behaviours. The themes were contrasted with the survey data collected from the same participants that perceived the ease of use and usefulness of the LAD in their team learning.

3.5 Ethics

As part of the requirements of this doctoral research, there were a total of three ethical protocols sought that are associated with the studies in Chapters 5, 6 and 7. Ethical approval for research aim one in Chapter 4 of the thesis is exempt, as it does not include human subjects and their data and follows a different integrity protocol. In that chapter, Appendix C contains the included studies and the tables required for the methodology as part of the systematic literature review.

Ethical approval for research aim two and research aim three found in Chapters 5 and 6 in this thesis, respectively, is part of a project and the lead institution has given anonymised data, which has been exempt, as data had already been collected, archived and anonymised for analysis by the lead institution. The exemption has been issued by the University of South Australia (Application ID: 202765, approval date: 12/07/2022).

Ethical approval for research aim four in Chapter 7 in this thesis has been exempt, as data had already been collected, archived and anonymised for analysis by the University of Curtin, including log data, surveys and focus groups. The exemption has been issued by the University of South Australia (Application ID: 203250, approval date: 25/08/2021). For transparency purposes, the questions asked to learners for the technology acceptance model and the focus groups can be found in Appendix B.1 and Appendix B.2, respectively.

3.6 Overall Reflection

This study has four research aims. The first aim is to conduct a systematic literature review of small groups in technology-mediated learning (TML) settings. The review focuses on defining TML, exploring research methodologies, and identifying learning factors that affect team cohesion. The second aim is to examine team synchrony in TML environments using an analytics-based measure as a proxy for cohesion. The third aim is to explore team perceptions of their cohesion over time

and how their perceptions relate to their learning. The fourth aim is to develop and evaluate a LAD that helps teams monitor and regulate their collaboration based on their perceptions and interactions with the dashboard. Each chapter presents the results and discussion of each research aim, addressing gaps in the literature and offering insights on team cohesion and collaborative learning in TML settings.

This study aimed to fill gaps in the literature on cohesion within small groups participating in technology-mediated learning (TML) environments. The systematic literature review highlighted a lack of research on how group cohesion emerges in TML using temporal techniques, the reliance on survey instruments instead of trace data collection and analysis, and the need for teacher interventions to enhance group cohesion in online learning environments. To address these gaps, analytics-based measures were employed to understand team cohesion using group synchrony as a proxy, while characterising team cohesion perceptions based on their learning constructs. The study found distinctive relationships between teams' level of group synchrony, learning engagement, performance outcomes and feedback, indicating substantial implications for measuring cohesion indicators using log data collected from LMS. Additionally, the study highlighted the importance of supporting vulnerable teams in collaborative learning based on their cohesive perceptions and task cohesion. The development of a learning analytics dashboard (LAD) to aid collaborative learning experiences was explored, with the main finding that K-12 teams perceive the LAD as useful in supporting team regulation in collaborative settings, fostering engagement and collaboration.

The are several strengths and limitations that the research brings in this thesis. It provides recommendations for guiding team cohesion research to help support learning outcomes for teams in collaborative contexts. As such, LA approaches have practicalities in approximating cohesion, which can help to identify teams that may be struggling. In addition, the approach can be applied to team-based TML environments. The thesis demonstrates that cohesion can be measured and analysed using quantitative approaches as a proxy, as long as it is informed by

theory and practice. The SLR provides guidelines and recommendations for researchers that wish to continue the work. For example, potential research can include how LA tools and AI can support team cohesion in TML. Moreover, the studies have much potential to contribute to other domains not limited to WIL environments and contain eventlog data that capture team member interactions with an activity. However, the guidelines and recommendations are limited to small groups in TML and future work could contrast with communities or larger groups in TML. Moreover, some methodologies outline the thesis, such as the analytics-based measure, are not user-friendly and require significant domain expertise in data science and programming to make it functional. Some of the findings regarding the cohesive perceptions and relationships with learning constructs may not be generalisable across all learning environments, given the length and situation of the WIL environment. Lastly, LADs are not particularly known for providing effective feedback. As a result, researchers should vigorously test the team dashboard and examine if these LA tools provide consistent results.

Future work requires approaches that will help facilitate team cohesion in TML environments. As mentioned in the implications, it is not only important to measure and analyse cohesion, but to also consider how we can improve team cohesion in TML given the lack of studies. The team dashboard that was developed to address research aim four can play an important role by providing feedback to teams that improve their cohesion. The future also requires the applicable of using multiple sensors to build a holistic framework to measure and analyse cohesion using multimodal data that spans different types and contexts. For instance, using sensors to capture video, movement and audio data, that can be combined with genetics or profile data that helps to characterise team cohesion. Finally, the examination of how artificial intelligence can be used to measure and analyse the data and support team cohesion. Studies should focus on how AI impacts the cohesion of teams, given that AI is increasingly being integrated into areas with human activity.

As a reflection of the research process, the systematic literature review is one of the most rewarding and challenging studies I have done. I was inspired by the

amount of work done in the psychology domain, mainly the organisation sciences. There have been at least 100 years of research work, with many definitions, conceptualisations, and approaches to measure it. Given its massive importance on team performance and learning, I was interested to see how cohesion was shaped and the kind of work conducted in the collaborative learning context. To make this happen, I took inspiration from the many systemic reviews and adopted those conceptualisations and definitions to report on the current state in the educational context. It was nice to see a lot of comparable findings, such as the definitions used and how it was measured. But what really struck me was that the problems in organisational sciences were also relatable to the educational landscape, for instance, the lack of quantitative methodologies given that the digital learning environment provides ample opportunity to do such analysis. In a way, this was very much interdisciplinary research that benefited both fields.

The analytics-based measure study was a difficult study to do. Delivering an indicator or proxy for cohesion using a quantitative approach is rarely seen in interdisciplinary research. Identifying a potential algorithm was challenging, and much research needed to be done in these two fields to eventually find a possible approach, which recommended using a networking-based approach. But the challenge remained to work out what kind would be the best approach. After reading about the temporal characteristics of cohesion, which shows that teams with good cohesion will likely have good group synchrony, the idea of temporal network motifs came around. The properties of group synchrony describe important indicators of cohesion, such as the coordination and temporal interactions between members.

For the cohesive perception study, I think building from research aim two is very important. I was interested in seeing if these temporal motifs can characterise a team's cohesive perception, such as if they are in dissonance or consonance. To my surprise, the data showed some links, which was exciting. High engagement, good performance, and teams with similar cohesive perceptions (in consonance) had higher occurrences of triadic motifs, which were indicators of potential cohesion in my previous study.

This study regarding how teams interact with learning analytics dashboards came as an opportunity. It was another rewarding and challenging study, as I had to apply for extensive ethics, given the K-12 nature. I needed to collaborate with partners from regional areas to design and code up a dashboard from scratch. Then implement it for a course that was in another state while continuously improving it and hoping that everything goes well. Even though the study was not about measuring or analysing cohesion, it has implications. My previous studies can be incorporated into this dashboard to support cohesion and allow students and educators to monitor it. The most important finding I found in this study was that team members found it helped improve their dynamics by understanding how their team members were interacting with it. So, it gives me hope that this tool can play a role in improving team cohesion.

3.7 Summary

The methodology in this chapter provides an overview of the data sets, tools, techniques, analysis and ethics required to conduct and address the studies in this thesis. For Chapter 4, the method uses a systematic literature review adopting the PRISMA framework. Statistical summaries, bar plots, and cross-table illustrations are used to aid in interpreting the results. For Chapter 5, teams are clustered and distinguished based on how they engage with their learning materials in a WIL environment using a clustering technique. These groups are then characterised by their engagement and performance using a series of statistical techniques. Finally, the analytics-based measure uses temporal network motifs to examine group synchrony to characterise the clustered teams. For Chapter 6, a data-driven approach is used that includes surveys and log data to aid in the characterisation of team cohesive perceptions and their learning constructs. Finally, for Chapter 7, the technique uses a mixed-method approach that summarises log data, surveys and focus groups. Team perceptions are analysed concerning the impacts of the dashboard on their collaborative learning. The ethics section explores the protocols, emails, and applications this thesis covers.

Chapter 4

The cohesion of small groups in technology-mediated learning

This chapter presents the results of the systematic literature review to cover the breadth and depth of the existing body of work on cohesion in TML. The work addresses research aim one. The work described in this chapter has been published in the International Journal of Education Research Review (Zamecnik et al., 2022c), which covers how studies measured and analysed cohesion in TML. With the need to understand how researchers have conducted studies related to cohesion and TML, a systematic literature review was conducted to consolidate the research. The systematic literature review covers how team cohesion has been conceptualised, the methodologies used and emerging factors impacting team cohesion and learning.

4.1 Introduction

The first research aim is to report on a systematic literature review of small groups in TML settings. The technology-mediated learning definition was used as it implies that technology plays a more neutral role in the learning process and that it is a tool that is used to facilitate learning rather than something that

automatically improves it. The outcome of the research aim will address the gaps in consolidating team cohesion research in collaborative learning. Chapter 4 presents the results and discussion of the definitions, methodologies, and learning factors that influence or substantiate cohesion. As such, the study investigates the definition, measurement, and factors that influence group cohesion in technology-mediated learning (TML) settings. Specifically, it examines the most commonly used definitions and methodological approaches for measuring and analysing group cohesion and the factors that impact and facilitate it in TML environments.

Section 2.1 in Chapter 2 contains extensive literature that motivates the research questions in this Chapter. This study builds on previous work by expanding the knowledge of team and group cohesion and how it has been defined, conceptualised, and measured in collaborative TML environments. Moreover, examining how the factors impact and facilitate cohesion for small groups. As such, the study provides recommendations and guidelines for future research to advance cohesion in TML.

The methodology uses a systematic literature review approach, namely, the PRISMA framework (Moher et al., 2009), to identify, select and critically praise the research for answering the clearly formulated questions in this Chapter. The results of the critically appraised articles and the subsequent extracted information are interpreted using summary statistics and visualisations to aid in this Chapter's discussion.

The chapter is organised as follows, Section 4.1 introduces the current state of cohesion literature concerning TML. Section 4.3 contains the research questions that are addressed and Section 4.2 details the methodology. Section 4.4 provides the results and discussions. Section 4.5 provides knowledge gaps and recommendations providing the scaffolds required for addressing the remaining three research aims.

This chapter provides a literature synthesis on the definition, measurement, and analysis of cohesion in small groups participating in learning experiences, highlighting the gaps in the existing research. The main findings include a scarcity of

studies on group cohesion in technology-mediated literature using temporal techniques, a reliance on survey instruments instead of those collecting trace data, a lack of teacher interventions to enhance group cohesion in online learning environments, and a need for instructors to have tools to support the development of cohesion in groups over time. The chapter argues for the need for research in temporal and analytical-based measures that utilize log data to understand how group cohesion evolves, and the importance of validating claims of a design improving the cohesion of collaborative learning groups. The discoveries in this chapter helped formulate the remaining research aims that address the gaps identified in the systematic review.

4.2 Research questions

The review investigates the research methods and trajectory of group cohesion literature of small groups in technology-mediated environments. The following research questions are posed to address these aims:

- RQ1: What are the most commonly utilised definitions of group cohesion in TML setting?
- RQ2: What methodological approaches are commonly used to measure and analyse group cohesion of learners in technology-mediated environments?
- RQ3: What factors impact and facilitate group cohesion in technology-mediated environments?

4.3 Methodology

This section describes the research methodology used to investigate the research questions, including the research design, data collection methods, and data analysis procedures.

4.3.1 Study design

The systematic review follows the PRISMA framework (Moher et al., 2009) shown in Figure 4.1. The systematic literature review procedure was split into four phases: 1) Identification; 2) Screening; 3) Eligibility and; 4) Inclusion. The first phase involved a systematic search between 1995 to 2020 (inclusive) to derive the existing literature review. The first international bi-annual conference for computer-supported collaborative learning (CSCL) research took place in 1995 (Stahl & Hesse, 2006). It was known to be the first official source of literature related to collaborative learning incorporating technologies. Therefore, literature from that point onwards was used as a reference for the systematic review. Generic search terms such as: ALL = ("computer-supported collaborative learning" OR" online learning*" OR "distance learning") AND ALL = ("group cohesi*" OR" team cohesi*") were used to query the databases. The queried databases included: Scopus, Springer, Taylor and Francis, Science Direct, Wiley, Web of Science, Emerald, ACM and IEEE. Peer-reviewed papers were included if (a) group or team cohesion was a focal point, (b) they facilitated group cohesion in a TML environment, and (c) they used methods to evaluate group cohesion that has implications for learning. The review was limited to papers exploring cohesion in K-12 and higher education. Furthermore, extensive but constrained searches were required to minimise the risk of missing quality papers. Specifically, the identification criteria included team cohesion studies to avoid excluding papers that have examined group cohesion within teams. There is a risk that studies may overlap these terms interchangeably in educational learning contexts. Therefore, those studies are included if they meet the inclusion criteria of this systematic review.

4.3.2 Data analysis

This search process resulted in 1,809 records following the removal of duplicates. After completing the search, the second phase involved screening the title and abstract using the Covidence systematic literature management tool[1]. Features of

[1]Covidence management tool

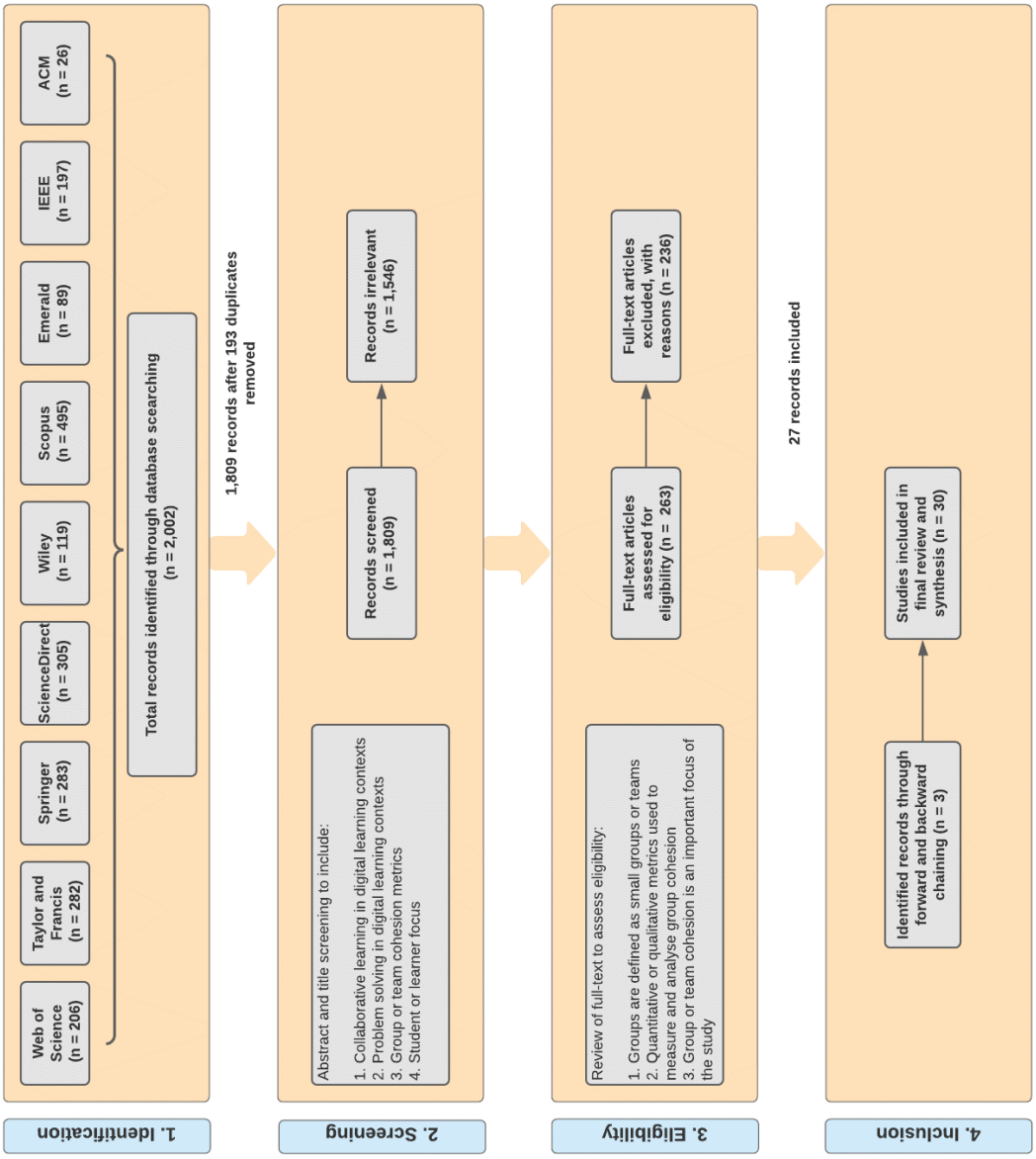


FIGURE 4.1: Overview of the Systematic Literature Review Process (Zamecnik et al., 2022c)

the tool were used, such as highlighting relevant keywords to streamline the screening process. For cases where the title and abstract descriptions did not indicate relevant papers, they were examined in detail by reading the methodology and results. Two reviewers coded 350 papers during this phase in 3 iterations, which resulted in the inter-rater agreement of 0.42, 0.63 and 0.88 Cohen's Kappa (Cohen, 1960)., respectively. The screening process for article selection involved three iterations, with each iteration including 50, 100, and 200 papers, respectively, resulting in a total of 350 papers. To ensure agreement, conflicts were discussed

and resolved until a substantial agreement with a Kappa of 0.8 or greater was achieved. During this process, one conflict that arose involved the inclusion of community of inquiry studies and social presence, which were ultimately excluded due to fundamental differences between communities and small groups. Small groups have increased accountability, relationships, contributions, and dialogue compared to larger groups, which are more complex and can lead to counter-productive behaviours such as parasitism, social loafing, or misuse of resources. The final selection process resulted in 263 relevant full-text articles, which were thoroughly reviewed against the inclusion criteria. This process includes reading the papers in detail and selecting papers that align with the following inclusion criteria, where the study:

1. Presents original research, analysing group or team cohesion in TML environments.
2. K-12 and higher education in technology-mediated environments that compromises TML, i.e. computer-supported collaborative learning.
3. Was published in a peer-reviewed journal/conference proceeding, available in English,
4. Focused on quantitative, qualitative or a mixture of research methods to measure the dimensions of group cohesion (i.e. task or social cohesion).
5. Relied on log data, questionnaires or surveys used to validate or test cohesion and the study applies descriptive or inferential statistics and identifies findings that have implications for collaborative learning.
6. Includes only small groups, e.g. 2-10 members per group.

Following this procedure, 236 papers did not meet the selection criteria and were not considered for final extraction. The fourth and last step involved manual forward and backward chaining of selected papers (n = 27) to minimise the risk of missing papers. This procedure added 3 papers that met the screening and eligibility criteria. The final screening process resulted in 30 papers satisfying the

inclusion criteria in this review. The breadth of the search extended to conference papers driven by the limited number of journal articles included in the review. The inclusion of conference papers was also strongly aligned with the review's goal as they yielded important information about how researchers used novel approaches to link group cohesion with collaborative learning. In the final stages of the systematic review, the selected 30 studies were critically appraised using the Joanna Briggs Institute (JBI) checklist with slight modifications to cater for the frame of reference for qualitative and quantitative research, cross-sectional and quasi-experimental accordingly (Lockwood et al., 2015; Moola et al., 2017; Tufanaru et al., 2017). All the selected studies were considered at minimum risk of bias and were promptly extracted for review.

Predominantly, the systematic review aims to discern the definitions, measures and methods used to analyse group cohesion in technology-mediated environments and their impacts on small groups' collaborative learning. Research aim one was addressed by synthesising the 30 systematically selected studies shown in Table C.1 to C.5. Each study examined how authors measured the dimensions of cohesion (e.g. task cohesion, social cohesion, belongingness, group pride and morale), including the level of measurement and analysis used for individuals and teams. The summary of the codes regarding cohesion measures, such as the focus on measurement, analysis and conceptualisations, can be found in Table 4.2. The codes were adopted and framed similarly from an existing literature review that measured team cohesion (Salas et al., 2015). The motivation for adopting a similar approach was two-fold. Firstly, a peer-reviewed approach must be established to help code the results. Secondly, the coded metrics align with the methodology to help answer the research aim. Thus, the papers were coded as part of the review using the adapted methodology, keeping the same definitions used in contemporary literature concerning the inclusion criteria and research questions.

In addition to the adopted methodology, the review captures the common methods used for analysing group cohesion, including obtrusive, unobtrusive or mixed methods. Further, the data collection formats researchers used, such as surveys, log data or a mixture of both, are also drawn. The study type, e.g. longitudinal,

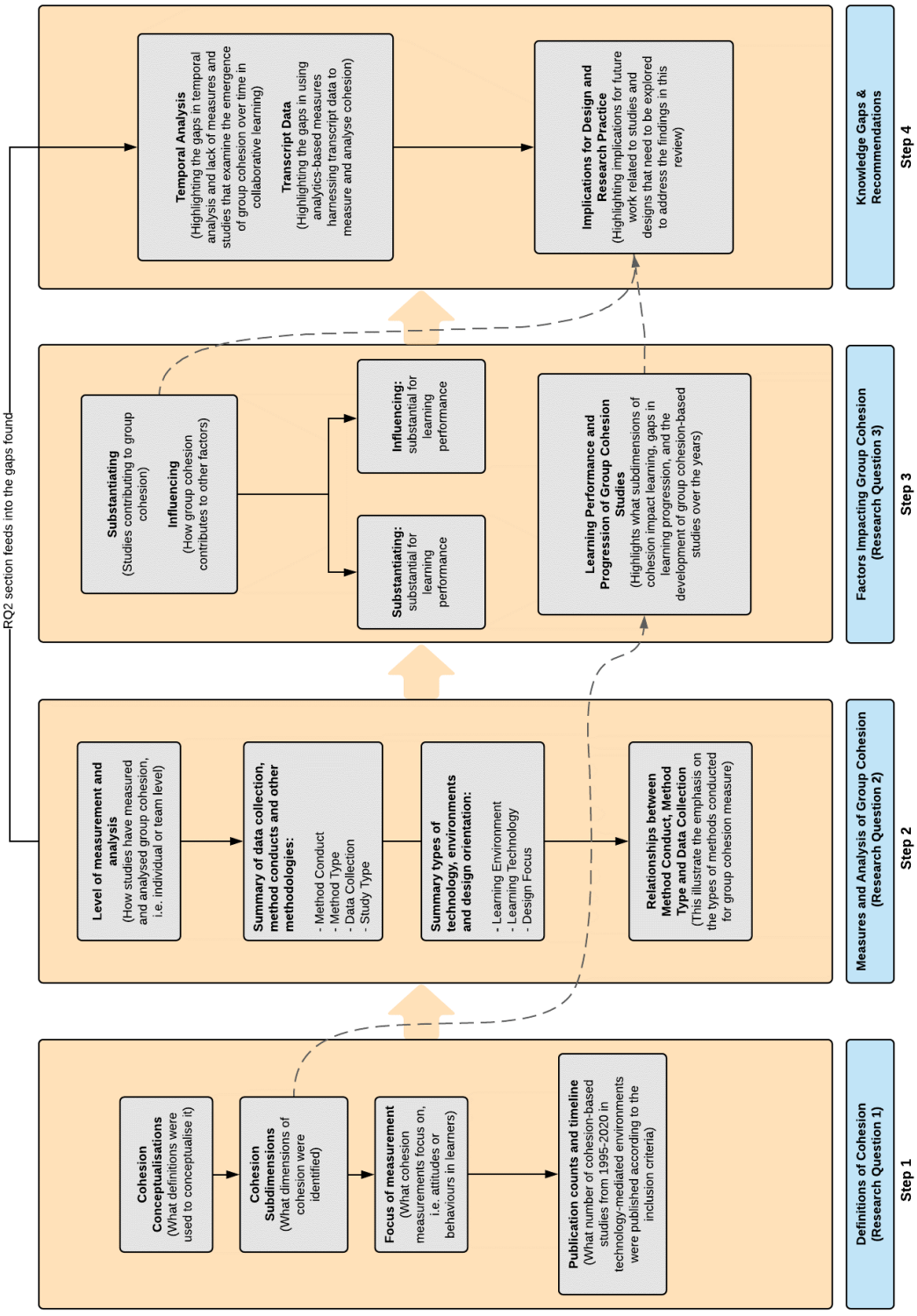


FIGURE 4.2: Workflow of the Systematic Literature Review Structure and Processes (Zamecnik et al., 2022c)

cross-sectional or design-based research and statistical approaches, were included

in the coding scheme to further understand how research is conducted. Furthermore, factors that had potential implications for group cohesion and whether they impact performance in TML settings were collected. These are categorised into factors (i.e. substantiating and influencing, see Figure 4.2) by synthesising them through cue cards, comparing, contrasting and critically evaluating the selected literature. The study's generalisability, implications, and limitations were coded and examined to view the progression of the field. The population and group sizes, along with the duration of each study, were recorded and summarised. Overall, the findings across the extracted literature were critically evaluated to uncover insights. The workflow structure of the systematic review process can be seen in Figure 4.2.

4.4 Results and discussion

4.4.1 Summary of selected studies

Table 4.1 shows the type of publication, educational level, study period, group size and population in the selected studies (Table C.1). It can be observed from Figure 4.3 and Table 4.1 that the majority of the studies have been published in journals (69%) and a lesser extent, at conferences (31%). The papers published in journals and conferences from 2003 to 2020 seem to be equally spread over time. While the number of studies oscillated between 1 and 3 from 2010, there has been a noticeable growth starting in 2018. This growth may signify an increased interest in group cohesion studies. No papers from 1995 to 2002 met the inclusion criteria.

The educational level seen in Table 4.1, shows the selected studies predominantly consisting of students in higher education (100%) and less with K-12 education (0%). Moreover, a large portion of studies shows students studying between 10 and 16 weeks (60%) and between 1 and 8 weeks (27%), while studies that were over 16 weeks (10%) were less common. Group sizes were mostly between 3 to 5 (47%) students, with fewer studies containing 4 to 6 students (37%). The majority

TABLE 4.1: Overview of the summarised studies containing publications and student population, group sizes and their duration of study

Data Description	Publications Count	%
Type of Publication		
Journal	20	67
Conference	10	33
Education Level		
University	30	100
K-12	0	0
Period of Study		
1-8 Weeks	8	27
10-16 Weeks	18	60
>16 Weeks	3	10
Unknown	1	3
Group Size		
2-10	1	3
3-5	14	47
4-6	11	37
5-7	4	13
Student Population		
0-25	2	7
25-50	9	30
50-100	7	23
100-200	7	23
200-450	5	17

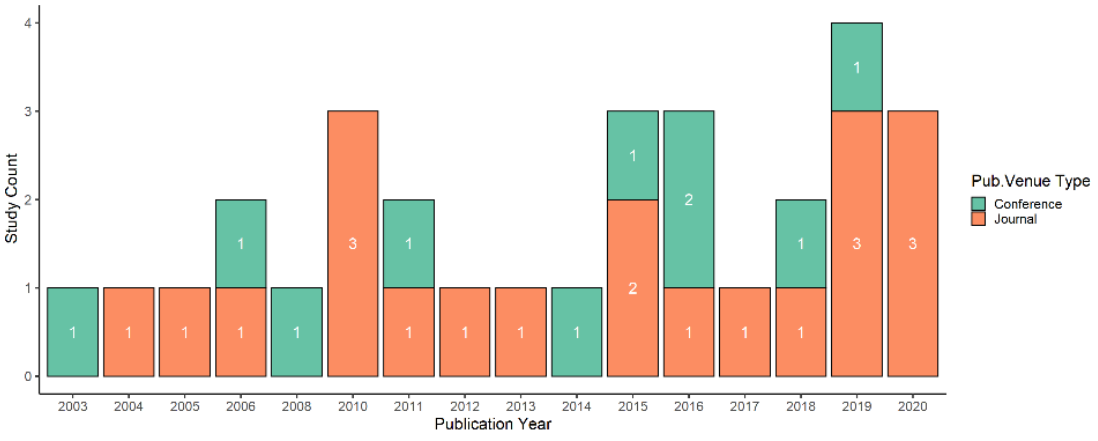


FIGURE 4.3: The frequency of studies per year and which venue the papers were published (Zamecnik et al., 2022c)

of studies had group sizes with smaller ranges (e.g. 3-5, 4-6 ,5-7), one study had group sizes ranging from 2 to 10 students (3%). Typical student population sizes ranged between 25 to 50 (30%), 50 to 100 (23%) and 100 to 200 (23%) in the selected studies. To a lesser extent, other studies contained between 0 and 25

students (7%) and also 200 to 450 (17%). All studies shown in the table were conducted in a university setting.

Figure 4.4 shows that most selected studies included students from Management, Education, Technology and Computer Sciences courses. The smallest studies involved Human Resources, Marketing, Mathematics, Language and Psychology students. Interestingly, many studies involving Technology and Computer Science courses have been published at conferences. This finding is not surprising, as studies published within conferences frequently blend statistical methodologies with computer education that involve students studying technology or computer-based subjects.

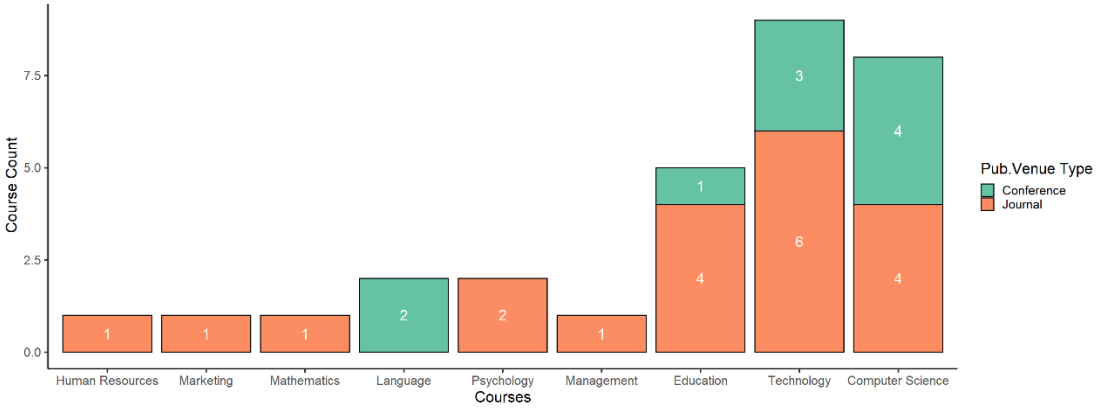


FIGURE 4.4: The frequency of courses where group cohesion studies are undertaken and to which venue the papers were published (Zamecnik et al., 2022c)

Looking at journals, most studies involved students from Mathematics, Psychology, Management, Education and Technology related courses. Observing the student disciplinary areas, substantial heterogeneity based on the courses where researchers examined computer learning and group cohesion is seen. The review also shows some striking results regarding the level of education under study. All studies included in the review focused on higher education, with none of the included studies analysing the K-12 context. Such disparity is a significant concern and demonstrates a gap in the literature for TML of small groups. Learners are increasingly developing 21st-Century skills in K-12 education, such as collaborative learning and problem-solving skills in environments driven by digital learning (Pellegrino, 2017). Developing these skills is important as examining group cohesion

within these contexts is crucial to understanding how small groups build relationships and work effectively. Future studies should examine K-12 education more closely to understand how cohesion develops in these contexts.

4.4.2 RQ1: Definitions of group cohesion

The adopted definitions of cohesion within the included studies were examined to explore how group cohesion has been conceptualised. Table 4.2 shows the group cohesion concepts, dimensions and the focus of measurement. The cohesion conceptualisation of the selected studies shows that (57%) are found to be multidimensional, (23%) unidimensional and (20%) as unknown. In Figure 4.5, it can be observed that the group cohesion concepts are becoming more multidimensional from 2015 and less unidimensional, indicating a shift from the latter. The findings confirm that this trend is also present within TML environments, signifying the increasing conceptualisation of the multidimensional concept for group cohesion studies (Chang & Bordia, 2001; Salas et al., 2015). Table 4.2 also shows the task, social, and belongingness dimensions of group cohesion were most widely used with (30%), (16%), and (32%) as seen in the table, respectively. However, the dimensions of group pride (2%) and morale (8%) are not widely studied in TML contexts.

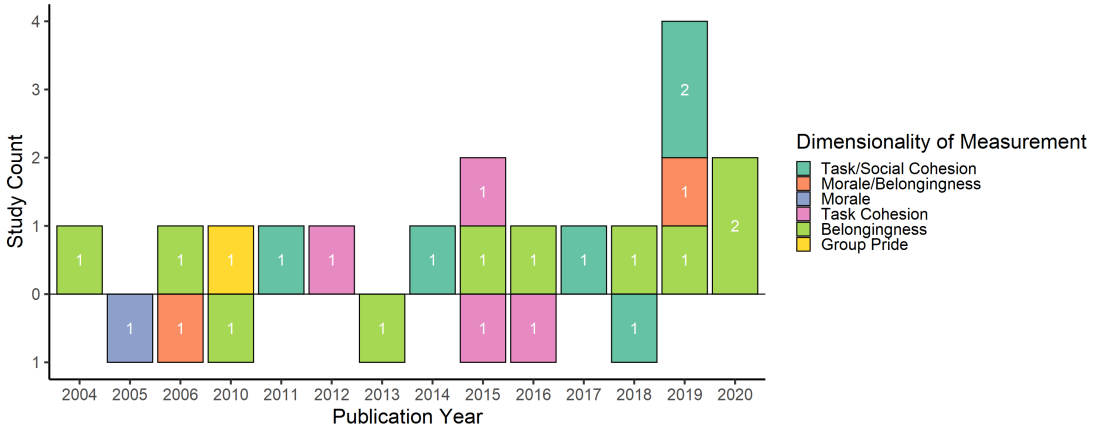


FIGURE 4.5: The frequency and publication year of multidimensional (above the horizontal line) and unidimensional studies (below the horizontal line) (Zamecnik et al., 2022c)

Besides the dimensions of cohesion, a mixture of attitudes and behaviours (53%) represented the most frequent focus of the included studies. The dimensions of group cohesion, mainly social, task and belongingness, have seen vested interest from 2015 and onwards in technology-mediated education. The findings show what researchers focus on regarding measurements of group cohesion. These results also show the increasing utilisation of these dimensions in the organisational literature, according to Salas et al. (2015) team cohesion review.

TABLE 4.2: The summary of definitions, dimensions and focus of measurement

Data Description	Publications Count	%
Cohesion Conceptualisation		
Unidimensional	7	23
Multidimensional	17	57
Unknown	6	20
Group Cohesion Dimensions (n = 37)		
Task	11	30
Social	6	16
Belongingness	12	21
Group Pride	1	2
Morale	3	8
Unknown	3	12
Operationalisaton/focus of measurement		
Attitude	4	13
Behaviour	5	17
Mixed	16	53
Unknown	5	17

Note. n refers to the total number of dimensions found in the selected studies.

Besides the noticeable increases in the task and social dimensions in this review, the finding suggests considerable interest in measuring the emotional connections between individuals of a team. An explanation for this phenomenon can be related to issues present in TML contexts, such as identification within the group, working in small groups, building trust, having accountability, increasing motivation, maintaining goals and the overall design of the learning environment (Bilgin & Gul, 2020; Hansen, 2016; Lu & Xie, 2018; Rogers & Lea, 2004; Tseng & Yeh, 2013; Williams et al., 2006; Yilmaz & Yilmaz, 2019). However, other dimensions, such as group pride and morale, are not extensively studied in the reviewed literature concerning TML. This finding also aligns with Salas et al. (2015) review,

where these dimensions are also limited in other fields (i.e. sports, professional work, military and other organisational literature). Moreover, the existing studies primarily rely on survey data. The data shows only 1 out of 5 studies have been defined and conceptualised according to the dimensions noted in this review using log data. On the other hand, the four studies with a mixture of log and survey data have only been examined from the survey point of view and not from the learner's trace logs. As a result, there is an obvious gap in the existing literature that would elaborate on the approaches to conceptualise and measure team cohesion using unobtrusive approaches, such as relying on event log multimodal (e.g., sensors) data.

In terms of operationalisation/focus of measurement, the findings show that they are predominantly mixed, capturing learners' behaviour and attitudes in groups. Researchers tend to understand how both factors impact group cohesion. Attitudes are often associated with behaviours, and research shows that attitude is used to understand the relationship of future behaviours (Glasman & Albarracín, 2006). The existing researcher also explores what occurs in TML platforms relating to the learner's cohesion, such as the future motives and participation within a group and what group members think about their peers (Gupta & Bakker, 2020; Wang & Hong, 2018; Wang & Hwang, 2012; Zheng et al., 2014).

Based on the five common sub-dimensions identified by Salas et al. (2015) and the results of the review, the findings show that no studies have explored a combination of all five group cohesion dimensions (i.e., task cohesion, social cohesion, belongingness, morale and group pride). There are several instances where studies have paired task and social cohesion or belongingness and morale dimensions. For example, how the roles impact task and social cohesion dimensions, collective task value and socially shared regulated learning (Wang & Hong, 2018; Zheng, 2017b; Zheng et al., 2014) and how belongingness and morale impact self-regulation of learning in collaborative groups (Xie et al., 2019). Conceptualising and choosing the dimensions depends on the research problem context. For instance, whether the task at hand allows group members to express their belongingness and how such information can be captured. Similar to other complex dimensions, such as

group level of allegiance (group pride), their level of confidence (morale), synchrony and exchange (social cohesion), and their commitment to achieving the group's goals (task cohesion). Future studies in collaborative learning are encouraged to explore the relationship between the sub-dimensions and be aware of logistical challenges to facilitate them.

4.4.3 RQ2: Measures and analysis of group cohesion

TABLE 4.3: The summary levels of measurement and analysis for examining group cohesion

Data Description	Publications Count	%
Level of Measurement		
Individual	5	17
Group	6	20
Mixed	19	63
Level of Analysis		
Individual	3	10
Group	17	56
Mixed	10	34

The results in Table 4.3 show the level of measurements for group cohesion studies in TML contexts is primarily mixed (63%), i.e. measuring both the individual and group. This finding suggests that researchers adopt a multilevel view of cohesion for measurement. Moreover, the results show that the level of analysis occurs at the group (56%) and mixed-level (34%), while individual analysis (10%) is to a lesser extent. The findings in this review suggest that researchers who study group cohesion mainly measure aspects of individual and group work as one package. Then are analysed based on the overall group using the statistical approaches outlined in Table C.5, to better understand attitudes and behaviours and performance in collaborative learning. Similarly, Salas et al. (2015) review of team cohesion in organisational literature found that multilevel approaches yielded better results in cohesion-performance relationships and that the analysis of teams yielded more significant findings than any other composition. Overall, the reviewed literature

consistently values the idea that multilevel approaches effectively measure and analyse group cohesion.

TABLE 4.4: The summary of data collection, method conducts, design, and other research methodologies used in measuring and analysing group cohesion

Data Description	Publications Count	%
Method Conduct		
Obtrusive	20	66
Unobtrusive	5	17
Mixed	5	17
Method Type		
Quantitative	25	84
Qualitative	1	3
Mixed	3	10
N/A	1	3
Data Collection		
Survey	20	67
Archival	5	17
Mixed	4	13
N/A	1	3
Study Type		
Longitudinal	2	7
Cross-sectional	25	86
Design Based-Research	2	7
Learning Environment		
Online	17	57
Blended	13	43
Learning Technology		
Learning Management System	24	80
Media Communication	4	13
Agent Based	2	7
Design Orientated		
Yes	9	30
No	21	70

Table 4.4 shows the research methodology commonly used for group cohesion studies in technology-mediated collaborative learning environments. The overview of these studies is seen in Table C.3 - C.5. The results show that the reviewed studies tend to adopt obtrusive (66%) and, to a lesser extent, unobtrusive (5%) and mixed (5%) approaches to measure and analyse group cohesion. The type of methods surrounding the conducts are inherently quantitative (83%) and, to a lesser extent, mixed, qualitative and quantitative (10%). Data collection methods are typically survey-based (66%) and mixed (14%). In contrast, log data (17%)

collection methodologies are not widely adopted in contemporary literature. The study types are predominantly cross-sectional (86%) and, to a lesser extent, design based-research (7%) and longitudinal (7%).

The learning environments identified across the 30 selected studies in this review consist of blended learning (43%) and online learning (57%). The former considers students in a blend of collaborative face-to-face and computer-based learning technologies on and off campus. The latter considers collaborative learning through virtual, distance-based or education delivery primarily online. Moreover, the learning technologies across these studies are mainly LMS (80%), with media communication (13%) and agent-based learning (7%) to a lesser extent. The findings also show that only 30% of the studies include a design-based technological implementation in conjunction with the measure and analysis of cohesion in the learning environment. Moreover, only 2 out of 30 studies have undertaken design-based research, specifically facilitating a technological implementation to directly support and analyse group cohesion. The limited number of studies indicates a clear gap where researchers have not focused on developing tools incorporated into the learning environment to help cohesion in collaborative learning contexts as part of design-based research iterations.

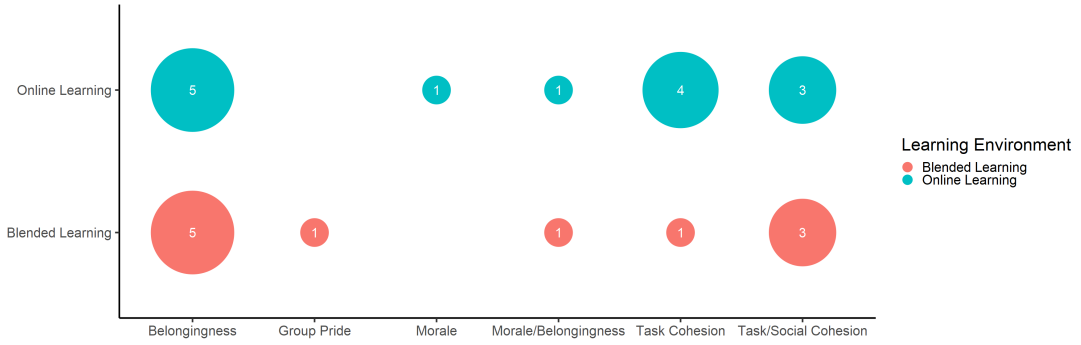


FIGURE 4.6: The frequency of the extracted studies from the blended and online learning environments as seen on the y-axis compared to the dimensions of group cohesion (see Table 4.2) along the x-axis. (Zamecnik et al., 2022c)

The frequency of the extracted studies from the blended and online learning environments, as seen on the y-axis compared to the dimensions of group cohesion (see

Table 4.2) along the x-axis, is shown in Figure 4.6. The existing literature measuring and analysing the dimensions of cohesion is relatively even between online (n = 17) and blended learning (n = 13) environments. This finding indicates that researchers who measured group cohesion in either environment focused on similar cohesion dimensions (see Table 4.2). The rationale behind this notion is related to the findings that all collaborative settings found in this review, regardless of the learning environment, are through learning technologies using computing devices, such as desktops, laptops or mobile. Overall, the relevance of the findings is important. It shows that the research interest of both environments is the same in this review.

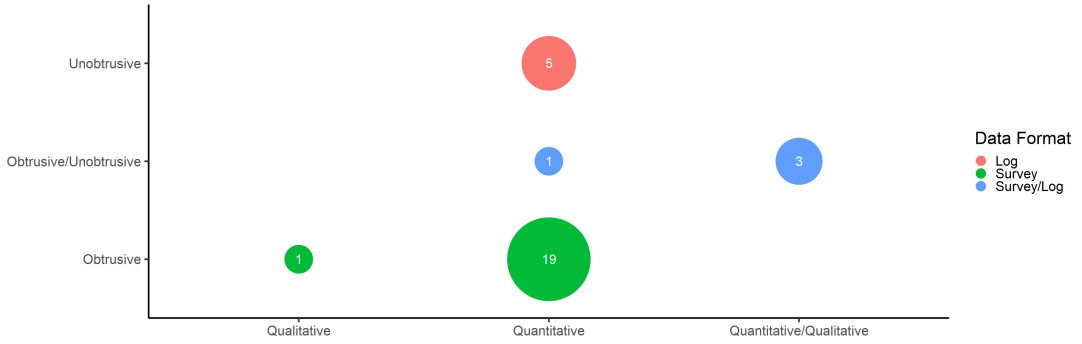


FIGURE 4.7: The frequency of research methods, data formats and their association with research measures (i.e. obtrusive, unobtrusive or mixed-method conducts) applicable from the extracted results in Appendix Table C.4 (Zamecnik et al., 2022c)

The frequency of research methods, data formats and their association with research measures (i.e. obtrusive, unobtrusive or mixed-method conducts) coincides with the extracted results in Table C.4. The additional results were gathered to observe the interrelations between method conduct, method type and data collection illustrated in Figure 4.7. The finding shows that out of the 29 reviewed studies, only three use qualitative and quantitative methods utilising survey and log data. The quantitative research methodologies represent the largest portion of the review studies (n = 25). As such, the data collection methodologies were largely survey-based (n = 20), whereas log data and mixed (n = 5) and (n = 1) were, to a lesser extent, respectively. The method conducted for log-driven data

were unobtrusive (n = 5), while mixed conducts were a combination of survey and log data collection approaches (n = 4).

An important aspect of measuring group cohesion in this review includes understanding how the data drives the research. For example, considering the type of data, collection methods and the nature of the use to understand group cohesion. Findings show that methodologies are mainly obtrusive due to the large number of surveys recorded in the reviewed studies (Beranek & Martz, 2005; Bilgin & Gul, 2020; David et al., 2006; Galyon et al., 2016; Garcia & Privado, 2020; Guo et al., 2019; Hansen, 2016; Lam, 2015; Rogers & Lea, 2004; Shin & Song, 2011; Tseng & Yeh, 2013; Wang & Hong, 2018; Wang & Hwang, 2012; Williams et al., 2006; Yilmaz & Yilmaz, 2019; Yilmaz et al., 2020; Zheng, 2017b; Zheng et al., 2014). The results suggest that quantitative research is the main methodology adopted to study group cohesion more than qualitative, as seen in Figure 4.5. Another interesting finding is that many studies are cross-sectional, e.g. studies taking place at a single time and examining specific variables. Studies, including longitudinal and design-based research, are very few. However, in Figure 4.5, the connections between the research methodologies are illustrated to gain a more in-depth perspective. The findings show that the selected literature regarding using event log data and mixed data in quantitative-based research using unobtrusive approaches to measure group cohesion is limited in digitally enabled education. Similar issues are found in organisational literature regarding the limitations of studies that include log data and unobtrusive methods to understand the development of cohesion (Salas et al., 2015). This contribution is significant as there are clear gaps across some fields where researchers have not closely investigated cohesion using log data, e.g. trace data of teams, that examine their behavioural and cognitive actions using unobtrusive methods.

The dominant data collection methodologies to measure and analyse group cohesion are quantitative-based surveys. Researchers use quantitative surveys such as Likert scaling to quantify group cohesion. Although four unique articles found in the review had taken advantage of the data from student learning platforms

and incorporated both survey and log data. The latter had a mixture of quantitative and qualitative data to measure group cohesion (Castro-Hernandez et al., 2015; Castro-Hernandez et al., 2016; Gonzales et al., 2010; Xie et al., 2019). However, no instances where the utilisation of log data such as student engagement was validated using a survey instrument to measure and analyse group cohesion. This finding shows a missed opportunity to help establish a link between how learners' behavioural and cognitive actions, including their communication within the group, can be used as an indicator to help understand the development and level of cohesion in these TML platforms. As such, exploratory studies need to be conducted to incorporate event log data from LMS and adopt LA approaches to establish how the learner's social and course engagement can indicate group cohesion in collaborative learning.

Survey data have been predominantly used to validate the static effects of cohesion, such as whether an intervention had improved group cohesion and group performance. However, a caveat of surveys is their inability to address group cohesion processes with high fidelity. Surveys are inherently static and often not reliable measures (Kozlowski & Chao, 2012, pp. 349), (Kozlowski & Chao, 2018, pp. 580), (Visser et al., 2000), as they are susceptible to a wide range of faults, such as coverage, sampling, nonresponse and measurement error described by Visser et al. (2000). Further, surveys interrupt continuous behaviours due to their obtrusive nature, such as forcing participants to stop and think while performing a task that may impact the way they answer the survey based on their current emotions and stress levels (Cook et al., 2002). As a result, surveys are substantially restricted in how they capture the development of group cohesion as a process. Group cohesion is a dynamic state that fluctuates, reciprocates, or stabilises over time in groups or teams (Braun et al., 2020; Kozlowski & Chao, 2012). Understanding group cohesion as a process requires different theoretical and methodological approaches relying on continuous data streams. In this review, no selected studies had utilised or undertaken research examining group cohesion as a process in TML environments. Future research needs to adopt studies that capture group cohesion

processes and use measures to highlight the dynamic changes in these learning environments and their impacts on collaborative learning and performance.

Evaluating the dimensions of group cohesion through the choice of survey or event log data depends on the context. For instance, using surveys to understand the effects or outcomes of an intervention for a control group in longitudinal or cross-sectional studies is a sound approach. On the other hand, using continuous data streams, such as log data, is more suited to understand temporal aspects, such as how learning processes or group cohesion changes over time in dynamic environments (Knight et al., 2017; Visser et al., 2000). Preferably, employing both approaches is ideal for gaining a richer understanding of group cohesion if logistically possible (Salas et al., 2015).

4.4.4 RQ3: Factors impacting group cohesion

Table 4.5 summarises the two most prominent factor groups, Substantiating (70%) and Influencing (17%), categorised from the selected studies in Table C.5. The Substantiating group concerns literature focusing on factors that considerably impact group cohesion. In contrast, the Influencing group concerns literature where group cohesion impacts other factors in technology-mediated collaborative learning contexts. For example, the factor Linguistics shown in Table 4.5 was used to quantify group cohesion. The two "*" symbols indicate that (n = 2) studies substantially impacted collaborative learning based on the factor. In terms of the eloquent effects of performance in collaborative learning, 10 out of 30 studies presented the relationship. Other studies (n = 4) were unsuitable for fitting within the two constructed groups in the table. Investigating the selected review is an important contribution, as there is limited research investigating factors that either help substantiate cohesion or whether group cohesion impacts other factors in TML environments. This discussion aims to critically review what knowledge has been generated over two decades in this area.

TABLE 4.5: The summary of identified factors that substantiates (contributes) to group cohesion and how group cohesion influences (impacts) other factors from the synthesised research

Identified Groups	Publications Count	%
Substantiating	21	70
Social interaction	4	13
Linguistic style matching **	2	7
Shared identity	1	3
Group similarity	1	3
Teamwork orientation *	1	3
Collective efficacy *	1	3
Communication quality	1	3
Cohesion-based feedback	1	3
Socially shared regulated learning *	1	3
Mastery goals	1	3
Collective task value *	1	3
Roles	1	3
Metacognitive support	1	3
Engagement *	1	3
Participation	1	3
Gaming *	1	3
Influencing	5	17
Satisfaction	1	3
Leadership	1	3
Engagement *	1	3
Communication	1	3
Trust	1	3
Other	4	13

Note. * indicates the number of factors that are substantial for performance in collaborative learning

4.4.5 Substantiating

The findings of the Substantiating factors include a large selection of reviewed literature (n = 19) that examines how psychological factors impacted group cohesion in TML. The findings show an assortment of factors that are sparely used, with the exception of social interactions (n = 4), linguistic style matching (n = 2) and gaming (n = 2). It can be gleaned from Table 4.5 that communication and interaction aspects, such as networks, linguistics, communication and participation, have been used to quantify group cohesion (Castro-Hernandez et al., 2016;

Galyon et al., 2016; Gonzales et al., 2010; Heo et al., 2010; Lam, 2015; Reffay & Chanier, 2003; Reffay et al., 2011; Wang & Li, 2008). These factors are important and noteworthy as there is a strong connection between cohesion and social elements within groups that impact teams. Furthermore, the group's identification, orientation, and roles have also been explored to understand their impacts on cohesion (Guo et al., 2019; Rogers & Lea, 2004; Williams et al., 2006; Zheng et al., 2014). Further studies such as collective task value, socially shared regulated learning, and metacognition are found to impact group cohesion substantially (Wang & Hong, 2018; Wang & Hwang, 2012; Wang & Li, 2008; Yilmaz & Yilmaz, 2019; Zheng, 2017b). Other interesting factors such as gamification, designs of online engagement, mastery goals and cohesion-based feedback in TML contexts to impact cohesion considerably (Altebarmakian & Alterman, 2019a, 2019b; Bilgin & Gul, 2020; Castro-Hernandez et al., 2015; Lu & Xie, 2018; Terzidou et al., 2016). Based on these findings, it can be observed that research regarding group cohesion-related studies in TML are very divergent and few. As a result, it is unclear if certain factors have more generalisability for effective group cohesion than others.

4.4.6 Influencing

The motivation for developing this factor group is to investigate how researchers examined the cohesion of small groups in digital learning environments that contributes to overall collaborative learning. For instance, examining the consequences of group cohesion in collaborative environments impacts students' learning. Based on the results, the Influencing group includes a small selection of reviewed literature (n = 5) that examined how group cohesion affects several factors in small groups' TML. Several factors such as satisfaction, leadership, communication, trust and engagement were examined in the reviewed literature (Garcia & Privado, 2020; Hansen, 2016; Tseng & Yeh, 2013; Xie et al., 2019; Yilmaz et al., 2020). The research investigating the benefits of group cohesion of small groups in digitally-driven collaborative learning environments due to the small number of studies found in the literature review is highlighted. This finding is important as it

demonstrates a knowledge gap about the lack of benefits group cohesion can have in digitally-driven collaborative learning environments. For instance, in face-to-face learning environments, it has been established that group cohesion increases productivity, quality of ideas, friendships and many other skills. However, it is assumed that this holds for students in TML and that the same trends apply in face-to-face environments. Consequently, the need to closely investigate and confirm the case and whether sufficient group cohesion in technology-driven platforms such as distance or online can build new skills not currently known in the literature. Further research is required to investigate and understand the consequence of group cohesion in TML environments that focus not only on performance indicators alone.

4.4.7 Learning performance

An analysis was undertaken to understand what factors are associated with group performance. The importance of such research is to provide insights regarding factors known to increase the overall collaborative learning experience in technology-mediated contexts. Based on the 30 papers in the analysis identified, only ten had meaningful impacts on collaborative learning performance. The identified factors related to these studies are SSRL, engagement, gamification, teamwork orientation and linguistics (Altebarmakian & Alterman, 2019a; Bilgin & Gul, 2020; Castro-Hernandez et al., 2016; Gonzales et al., 2010; Terzidou et al., 2016; Wang & Hong, 2018; Wang & Hwang, 2012; Williams et al., 2006; Xie et al., 2019; Zheng, 2017b). A commonality between the studies that show substance with collaborative learning outcomes have measured group cohesion as dimensions of task (n = 2), task/social (n = 3), belongingness (n = 3), belongingness/morale (n = 1) and group pride (n = 1). Only task cohesion, group pride, and belongingness impacted collaborative learning performance. Interestingly, the findings show that social cohesion had no associations with collaborative learning outcomes. For example, high social cohesion can lead to lower academic results in collaborative groups (Castro-Hernandez et al., 2015; Heo et al., 2010; Zheng et al., 2014).

Recent studies in team learning by Dimes et al. (2021) found that the team's learning is considerably better if social cohesion is optimised with task cohesion. To facilitate effective design in future studies, researchers may consider developing collaborative learning environments that optimise or balance social and task interactions. However, based on the review, how these dimensions impact learning progression is unclear, as current methods heavily utilise static measures that focus on outcomes rather than behaviours or processes. For example, it is unknown how cohesion defined by dimensions (i.e. task or social cohesion) shown in Table 4.2 in groups emerges over time and impacts students' collaborative learning in technology-mediated environments.

4.4.8 Progression of research

Recent trends of the reviewed studies show learning analytic approaches, such as tracing learners' data from LMS to understand their behaviours in TML contexts (Siemens & Long, 2011). LA is used to understand and improve students' learning outcomes by measuring and collecting their trace data (Siemens & Long, 2011). For example, engagement data such as social communication and task activity are used as behavioural indicators to measure group cohesion of learner groups (Altebarmakian & Alterman, 2019a, 2019b; Xie et al., 2019; Zheng, 2017b). A noteworthy study found in the reviewed literature by Altebarmakian and Alterman (Altebarmakian & Alterman, 2019b) had undertaken design-based research to understand group cohesion based on learner engagement in an online collaborative learning platform. Such studies are novel and essential in computer-supported collaborative learning literature, as they provide practical approaches to further understand the phenomena of collaborative learning in technology-mediated contexts through iterative designed-based research (Ludvigsen & Steier, 2019). Based on the trends, it is increasingly seen that behavioural indicators for group cohesion are becoming more critical in TML contexts. However, the rate at which this occurs, including the quantity and quality of studies produced, is somewhat limited in group cohesion studies from the review.

4.5 Knowledge gaps and recommendation

4.5.1 Temporal analysis

In teams, cohesion is an emergent process that develops over time and is a useful indicator of team characterisation (Kozlowski & Chao, 2012; Marks et al., 2001). Applying a temporal approach is one way to help reveal the journey of how group cohesion develops, including the learning processes and factors that impact them in TML contexts (Knight et al., 2017). An interesting finding of the systematic analysis was the lack of longitudinal studies from the reviewed literature (n = 2). This lack of temporal cohesion-based studies seems prevalent in organisational domains (Salas et al., 2015). However, this systematic review revealed that logistical constraints in TML contexts, e.g. learning platforms, have fewer data retrieval and quality obstacles than other settings where data collection is impossible (Lonn & Teasley, 2009; Romero et al., 2008). Learning platforms capture and store the footprints of learners in log data, which often contain temporal information, such as timestamps and events. Data from learning platforms are frequently analysed in LA using analytical strategies to understand learner behaviour and provide pedagogical support (Siemens & Long, 2011). The review has also shown that the selected studies have not utilised this capability to the full extent. For instance, the two longitudinal studies by Guo et al. (2019), Rogers and Lea (2004) have measured group cohesion with the support of survey information. However, log data to measure changes of group cohesion within a group were not used. This issue may be due to limited approaches to accurately analyse group cohesion based on behavioural and cognitive indicators over time. This circumstance can be attributed to the lack of approaches to measure group cohesion from temporal data. Another reason for researchers not utilising the data may be attributed to ethical limitations that prevent using log data or certain study constraints where that data is not needed. Overall, the studies considered in the review suggest a missed opportunity to understand further how group cohesion processes in technology-mediated environments evolve using well-established analytical techniques. Future research

in this context needs to consider examining group cohesion development and utilising temporal methodologies to understand the emergence of group cohesion and its implications for the student's overall collaborative learning.

4.5.2 Log trace data

A observation made in this review was the lack of log data to support the analysis of group cohesion in TML contexts. Findings show a limited number of studies (n = 5) out of 30 that strictly harness log data to measure group cohesion from engagement data (Altebarmakian & Alterman, 2019a; Heo et al., 2010; Reffay & Chanier, 2003; Reffay et al., 2011; Wang & Li, 2008). Researchers rely on surveys to measure specific dimensions of group cohesion such as task, social, belongingness, morale, group pride, and others. However, more research is required to enrich our understanding of group cohesion by using log data. In LA and EDM, log data collected from the traces of learner activity within a learning management platform has been used to understand the processes of learning (Wise, 2019). Research methodologies in this field often entail a mixture of qualitative and quantitative approaches to understand how students learn and behave in TML environments. For instance, the collected data is often used to measure individuals' cognitive and regulated learning abilities or the collaboration of groups to establish a connection with their learning outcomes (Baker & Inventado, 2014; Winne, 2017). Similar approaches can be applied to connect group cohesion development and the relationship with learning and performance. The benefits of such work will allow educators to support group members with minimal cohesion.

Log data has the potential to yield important discoveries of group cohesion processes where it would not have been possible using survey information. Furthermore, using event log data would allow for interesting insights when coupled with data mining techniques to increase the knowledge of the dynamics of group cohesion and how it connects with the learner's behaviours. Embracing only log data is not to say that measuring group cohesion with surveys or self-reports should phase out. On the contrary, surveys will have a crucial role in validating the novel

and methodological approaches to establish generalisability progressively with log data.

4.5.3 Limitation of the study

During the screening process, there were several challenges when reviewing papers that claimed to study group team cohesion in the educational context. Although many papers mentioned group cohesion in their abstracts or discussions, they did not explicitly conduct a study that analysed and measured it. Instead, these studies focused on related topics such as teamwork or social relationships. To ensure that only studies that specifically addressed group cohesion were included in the final analysis, a set of criteria was developed that papers had to meet. For example, papers had to explicitly define group cohesion, use a validated measure of group cohesion, and analyse the relationship between group cohesion and other outcomes. Each paper was carefully examined that met these criteria to ensure that it aligned with the research objective and inclusion criteria. By doing so, a set of rigorous studies were collected that provided valuable insights into the dynamics of group cohesion in various contexts.

The selected studies that were eventually included in this review presented additional challenges regarding the interpretations and the broader implications for group cohesion in TML environments. For example, the selected studies proved difficult to smoothly generalise contributions, as literature in this area is scarce. Some studies focused on factors such as behavioural indicators that can negatively or positively impact group cohesion, whereas other studies included design aspects that help facilitate cohesion. The issue was addressed by categorising them into groups and understanding how each study contributed to cohesion and improved other aspects of a TML platform. This way, it provides a valuable contribution regarding how studies in this area have progressed over the years.

4.5.4 Implications

For the past two decades, most researchers who studied group cohesion within a technology-mediated collaborative learning environment have measured and analysed cohesion as a static rather than a dynamic construct due to the extensive cross-sectional research. Given that cohesion is an emergent state that changes over time in groups, there are currently insufficient answers to address how it impacts individual members and their learning and performance progression. As such, it creates a problem for instructors. They have no tools available to identify, monitor, and provide pedagogical support for groups when cohesion levels lower, putting members at risk. The problem is further exasperated by the increasing challenges of online learning, where many teams learn autonomously at a distance with less support than traditional environments (Anshari et al., 2016; Wallace, 2003). Providing obtrusive surveys in such environments at regular intervals to a potentially large number of teams is highly inefficient and time-consuming (Visser et al., 2000). The expectation that group members will be motivated enough to complete them accurately is unrealistic.

A strand of innovation relates to producing novel assessment practices by utilising computational approaches in addition to instrument-driven ones (Hu et al., 2017). This important shift mirrors trends in computational social sciences (Lazer et al., 2009), where data is used to model and evaluate human behaviour, expanding the range of measures beyond established assessment instruments such as surveys. The computational psychometrics approach blends psychometrics and LA resulting in multimodal data, which provide granular construct evidence that would not be achievable using only one of the aforementioned approaches. This blend of psychometrics and LA, besides utilising various data sources (e.g., log data, assessments, and survey data, as well as from aggregated information), is specifically suited for near real-time assessment of learning processes and formative feedback purposes that will help measure and assess cohesion in collaborative groups.

4.6 Concluding Remarks

The definition and measurement of cohesion within small groups participating in learning experiences have been frequently studied. However, the research that conceptualises, measures and analyses cohesion in small groups was unknown. This chapter presents the literature synthesis and contributes to the gaps identified within the review with recommendations for future work. The main findings arising from this chapter reveals:

- Studies on group cohesion and how it emerges in technology-mediated literature using temporal techniques remain scarce.
- Research into group cohesion relies on survey instruments instead of instruments that collect trace data and methods to analyse them.
- A lack of teacher interventions that aim to enhance the cohesion of groups given the challenges of online learning environments.
- Gaps in providing instructors with the tools to support the development of cohesion in groups over time in TML environments.

There is a need to continually improve the learning environment of collaborative groups and identify what interventions enhance the cohesion of groups, given the challenges of online learning environments (Anshari et al., 2016). Only a few studies in this review have utilised design-based research methodologies to facilitate group cohesion. The review argues the need for research in temporal and analytical-based measures that utilise log data to understand how group cohesion evolves over time. In that way, instructors have the means to provide practical support grounded in evidence to help maintain group cohesion in an ever-changing environment. The second research aim in Chapter 5 focuses on an analytics-based measure using a temporal approach to examine the proxy of cohesion through group synchrony. The findings of the systematic literature review are also important from the standpoint of the third research aim in Chapter 6, focusing on how

to characterise the cohesion of teams based on their learning constructs contribute to this line of research. The argument of this review points to the limited studies that have taken steps to appropriately validate or test claims of a design improving the cohesion of collaborative learning groups. Furthermore, a gap in providing instructors with the tools to support the development of cohesion in groups over time remains to be addressed. As such, the fourth research aim in Chapter 7 contributes to this line of research. The discoveries identified in this chapter helped formulate the remaining research aims that address the gaps identified in the systematic review.

Chapter 5

Analytics-based measure for cohesion with temporal motifs

This chapter describes an approach for measuring and analysing the temporality of cohesion using the theory of group synchrony as a proxy. This work addresses research aim two. The work described in this chapter covers the analytics-based measure for cohesion using temporal network motifs. Given that cohesion is an emergent state that changes over time in teams, it is necessary to examine it using an analytics-based measure to capture its temporality. The approach will allow instructors to monitor and provide interventions to improve team collaboration and learning based on their emerging patterns of team behaviours related to cohesion.

5.1 Introduction

The second research aim aims to examine team synchrony in TML environments by using an analytics-based measure as a proxy for cohesion. This aim addresses gaps in measuring and analysing team cohesion using LA. In this Chapter, the results and discussion of the emerging team learning behaviours and challenges associated with measuring cohesion as a temporal construct in TML are presented. The

chapter explores the emerging patterns of team behaviours in learning engagement, investigates the association between these patterns and team performance, analyses the relationship between these patterns and group cohesion measured by temporal network motifs, and tracks changes in team cohesion over time using temporal motifs of interactions.

Section 2.2 in Chapter 3 contains extensive literature that motivates the research questions in this Chapter. The study builds on previous work in Chapter 4 by utilising an analytics-based measure to identify cohesion using group synchrony as a proxy. One of the important aspects identified is the development and application of unobtrusive temporal approaches that capture how cohesion emerges in teams over time. The study in this thesis focuses on the task cohesion of teams in a WIL environment.

The methodology uses a combination of data science techniques, such as K-means clustering technique, temporal network motifs and summary statistics to concisely answer the research questions in this chapter. Clustering is used to identify learning strategies of teams based on their engagement, while summary statistics are used to draw relationships with the patterns with performance. These insights are then connected with the results of the temporal network motifs to inform cohesion and how it changes over time during the teams study. Graphical illustrations are used to visualise the data for greater interpretability.

The chapter is organised as follows. Section 5.1 provides an overview of the problem and limitations in measuring and analysing the temporality of cohesion. Section 5.2 contains the research questions that are addressed and Section 5.3 details the methodology.. Section 5.4 shows the results of using an analytics-based measure. Section 5.5, 5.6 and 5.7 provide the study's discussion, implications and limitations, respectively. The chapter is concluded in Section 5.8 with a summary of the study

This chapter introduces a novel approach to measuring and analysing team cohesion using trace data from LMS in collaborative TML environments. The approach shows promising results in identifying relationships between teams' level of group

synchrony, learning engagement, and performance outcomes. It also establishes a relationship between synchronous interactions of team learning and cohesion, adding credence to the measurement. The findings suggest that this approach has substantial implications and generalisability for measuring cohesion indicators using log data collected from LMS, providing instructors with a way to monitor the cohesion of student teams while they are working on group learning activities. However, the results need to be reproduced to indicate generalisability in other contexts and validated using existing knowledge. The next chapter will utilise cohesion-based surveys with temporal network motifs to work towards generalisability.

5.2 Research questions

The focus on how teams in a WIL environment are defined by engagement with learning resources and their level of group synchrony using temporal network motifs to understand their cohesion. As a result, the study addresses four questions:

- RQ1: What are the emerging patterns of teams based on their learning engagement?
- RQ2: What is the association between emerging patterns of team performance?
- RQ3: How are the emerging patterns of team behaviours related to group cohesion, as measured by temporal network motifs of interactions?
- RQ4: How is the team cohesion, measured through temporal motifs of interactions, changing over time?

5.3 Methodology

This section describes the research methodology used to investigate the research questions, including the research design, data collection methods, and data analysis procedures.

5.3.1 Study design

The study took place in a global experiential learning platform developed by a major educational technology provider to develop employability skills. The platform provides team projects, mentoring, competency-based skills against a framework, work simulations, and professional development for the participants. The platform offers different learning experiences, but the analysis was restricted to one of its most popular offerings: a three-week, team-based program with a uniform course structure and content across the different cohorts. The analysis covers all cohorts from different higher education institutions between the end of 2018 and mid-2021. There were 30 sessions of the same program involving work on a real-world project, with 2,129 participants divided into 424 teams. Teams must strategise and work together by interacting with learning resources and completing their project. Teams will exhibit different levels of group synchrony within the online WIL platform. Every team is mentored, and their deliverables are reviewed and rated by an industry expert.

There is a deliverable expected for every end of the week in the form of a 'project plan' (end of week 1), 'project draft' (end of week 2) and 'final project report' (end of week 3). The reviewer will rate deliverables based on a specific list of criteria. Namely, the report has a clear outline, is professional, and aligns with the project brief. The reviewer rates deliverables (i.e. provides a score) for the project plan (week 1), draft (week 2) and Report (week 3) that teams must complete. Project and Assessment activities represent specific activities as part of the WIL platform. The former relates to activities to aid in the completion of the project.

The latter refers to Assessment activities that lead to the project submission. Each interaction with these activities by teams is recorded through the log data.

TABLE 5.1: Overview of the engagement activity types and descriptions

Activity type	Description
Orientation	Activities which introduce the program to students and welcome the students or give them an overview
Learning	Activities which are related to students learning or teaching course contents to students
Skills	Activities which are related to skill development, such as best practices in collaboration
Feedback	Activities which are related to feedback, such as client and mentor comments.
Project Draft	Activities which are related to drafting project, such as content related to drafting
Project Plan	Activities which are related to planning project, such as content related to planning
Assessment Draft	Activities which are related to submission of the draft for assessment
Assessment Plan	Activities which are related to the submission of the plan for assessment
Assessment Report	Activities which are related to the submission of the final report for assessment
Others	Other activities within the system apart from all above, such as registration, etc

Individual activities were grouped into activity types to provide a more robust analysis of the cohesion temporality. Table 5.1 shows the activity type categories and their descriptions of course materials that teams interact with weekly. As such, these activity types were categorised to provide meaningful interpretation of the extracted engagement metrics by closely following the program design of a major educational provider. For example, the Orientation activity type is categorised according to the associated description outlined in the table, that is, course material related to orientation (e.g., "Welcome to the program", "Learning Tips", "Preparation").

5.3.2 Data analysis

The K-means clustering analysis technique was used to identify emerging team behaviour patterns. Similar to the previous work in educational research (Barthakur

et al., 2021; Duff et al., 2020; Rodrigues et al., 2016), clustering was performed based on weekly team activities, counted for each of the variables presented in Table 5.1 and aggregated (i.e., averaged) at the team level. For instance, the count of project plan-related activities at the team level was obtained as an average of corresponding weekly counts per team member. The silhouette technique is used to evaluate the consistency of different clustering solutions to identify the optimal number of clusters. Meaningful and distinctive scores are crucial for clustering to draw more insightful conclusions compared to clusters with no discernible differences. It is important to note that both meaningful and non-meaningful clusters can have their own usefulness or limitations. Random placement can generate significant differences, but this may not reflect any underlying patterns in the data, resulting in arbitrary groupings. Therefore, to cluster the teams effectively and capture any underlying patterns, the silhouette technique was deployed, which provided meaningful insights into the analysis.

The K-means clustering technique used the learning activities as features to identify relationships between each team cluster that will help yield insights about their emerging team behaviour patterns. For example, what learning strategies teams adopt and the links it has to their performance and group synchrony. Finally, to visualise the clustering results, the factoextra R package was used, which provides 2-dimensional visualisation of clustering results using principal component analysis (PCA), a statistical technique for dimensionality reduction. The PCA biplot was used to help illustrate the clusters and interpret the clustering results. While Hidden Markov Models were considered for analysis due to their ability to describe and analyse sequences of events, K-means clustering was ultimately chosen as a better fit for addressing the research questions at hand. One aim of the study was to provide an overview of the behavioural patterns exhibited by teams on the WIL platform, and K-means clustering was deemed more appropriate for this purpose.

The next analysis stage involved applying temporal network motifs to each team cluster to characterise their group synchrony, which was used as a measure of team cohesion. Figure 5.1 shows an example of a directed multigraph graph. In social networks, the directed edge from node-to-node represents a connection

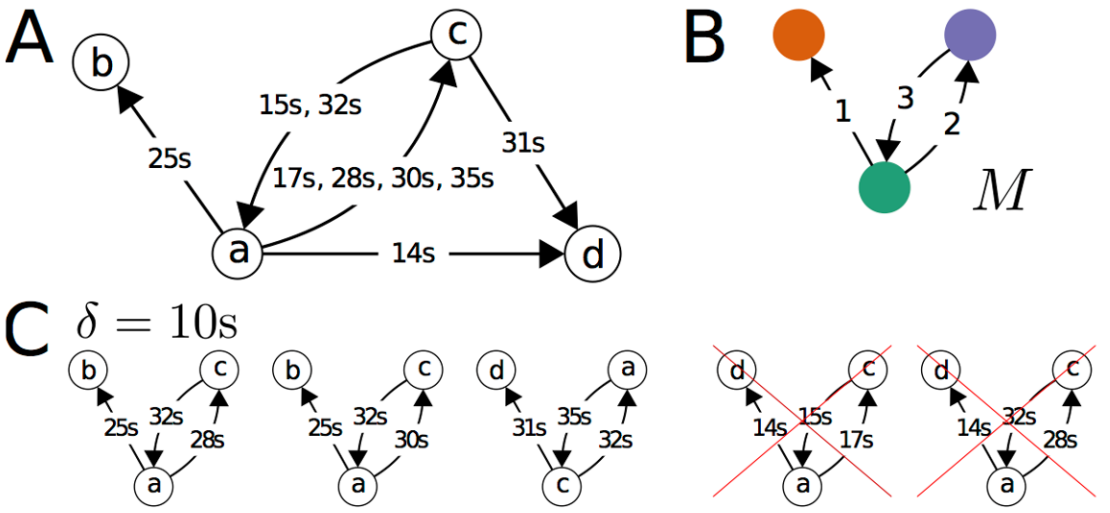


FIGURE 5.1: Illustrates the definitions temporal network motifs that have been defined and created by Paranjape et al. (2017), where A: represents a temporal network, B: represents the temporal motif and C: represents instances of motifs that confirm and do not confirm (crossed out) according to the motif in B. The crossed-out motif on the left side is negated due to an incorrect sequence, while the motif on the right is negated because it falls outside the 10-second (δ) time frame.

where communication has occurred from one node to another (i.e. one agent sends a message and receives a reply from another agent). In the context of this study, the network is defined differently to represent the synchrony of interactions with learning resources between team members. Each node is conceptualised to represent a team member (i.e. where nodes a, b, c and d are members of the same team of the same network) and the edges show the timestamped interactions with their learning resources based on the class activity labels seen in Table 5.1. That is, each edge formed has a timestamp when the successor node (node b) interacted with a learning resource from the same context as the predecessor node (node a), shown by the directed edge pointing from the predecessor (node a) to the successor (node c). In other words, a directed edge is shown for the member that follows on from another team member when an interaction has occurred with a learning resource.

The frequency of all 36 possible network motif instances in Figure 5.2 was examined for each cluster of student teams to identify temporal motifs. The values

were normalised as it is easier to interpret values between 0 and 1 compared to larger values in the thousands, reducing the risk of outliers and improving performance and interpretation. Although no information would have been lost if the original values had been retained, it would have been more challenging to interpret the data. The primary focus of the normalisation was on the distribution or proportion of the phenomena being studied. The Stanford Network Analysis Platform (SNAP) library (Leskovec & Sosič, 2016) for C++ was used, which is a general-purpose network analysis and graph-mining library. Specifically, the Temporal Motif Network module that takes as input the interaction data and counts the temporal motifs within the specified duration of time is applied (which in this case was one day). The decision to calculate motifs within each day is motivated by the nature of the target WIL program. Within this program, teams were expected to perform at least one engagement session per day with the learning platform. Overall, the analytical procedures outlined above will provide valuable insights into how each motif characterises each team cluster.

In Figure 5.2 by Paranjape et al. (2017), the matrix shows all temporal motif codes including all 2-node, 3-node and 3-edge (36 motifs $M_{i,j}$ in total) that are indexed by six rows ($_i$) and columns ($_j$). Given the high number of possible network motifs, they were grouped into five groups based on the key characteristics of interaction within them, as depicted in Figure 5.2. The blue colour presents all four Dyad motifs that capture a pair of students (orange and green) interacting with the same learning resource. The light blue represents three possible Switch Triad motifs, where two members (orange and purple) have engaged with a learning resource previously engaged by a third team member (green). However, these two members (orange and purple) have not engaged in the same resource. The red represents six possible Chaotic Triad, where three members represent three team members (green, orange and purple) engaged on the same resources in a non-sequential order. The orange colour represents two possible Ordered Triad motifs, where three members have engaged on the same resources in sequential order. The non-highlighted represents 21 possible Star Triad motifs that follow

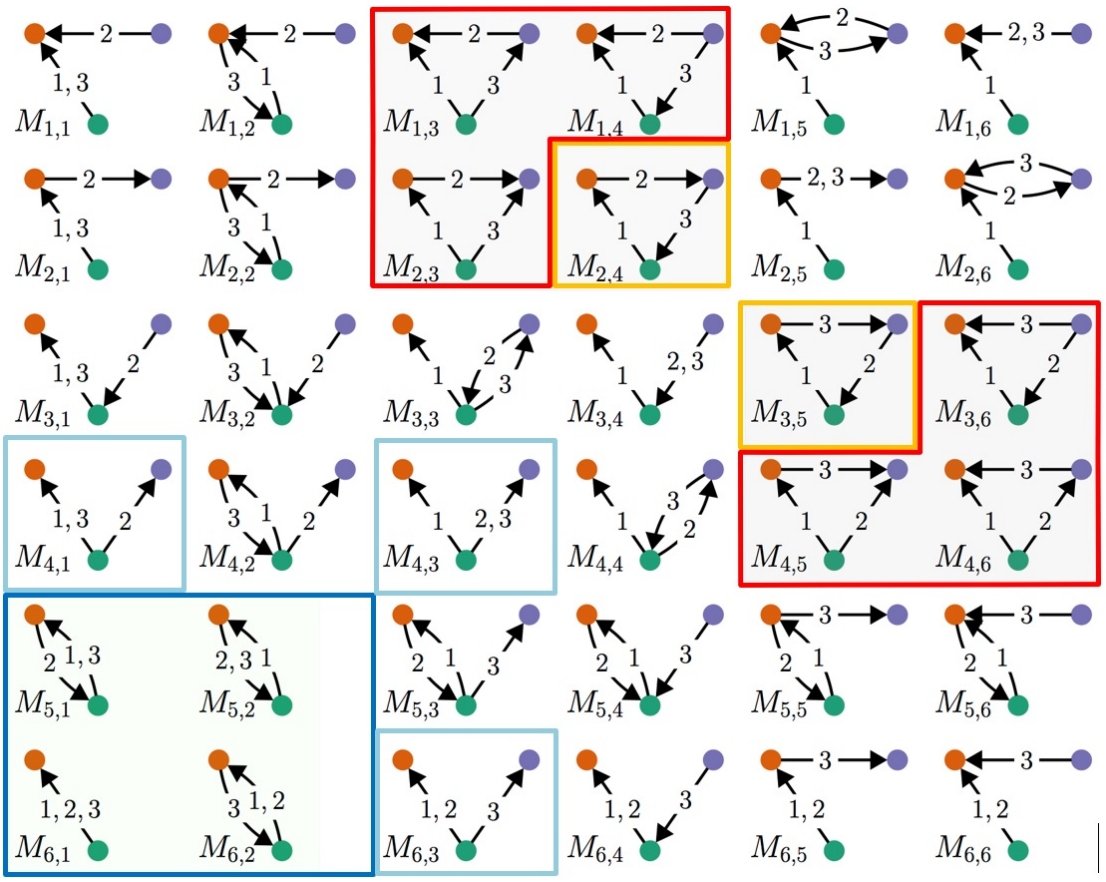


FIGURE 5.2: Grouping of temporal motif codes into five motifs group, where four are highlighted and one is transparent (Paranjape et al., 2017).

the same description as Switch Triad, except that only two members (i.e., green, orange or people) interact with the same learning resource.

After clustering and network motif extraction, a series of statistical analyses are conducted. Simple descriptive statistics were used to characterise each emerging cluster of team behaviour. Non-inferential statistics were used to examine the differences in team performance. The temporal motifs were grouped to understand how they characterise each team cluster and how those motifs emerge over time, respectively. The Kruskal-Wallis test was used to examine the difference in performance and network motifs between clusters, and significant tests were followed by a post hoc analysis using the Dunn test.

5.4 Results

RQ1: Emerging patterns of team behaviours

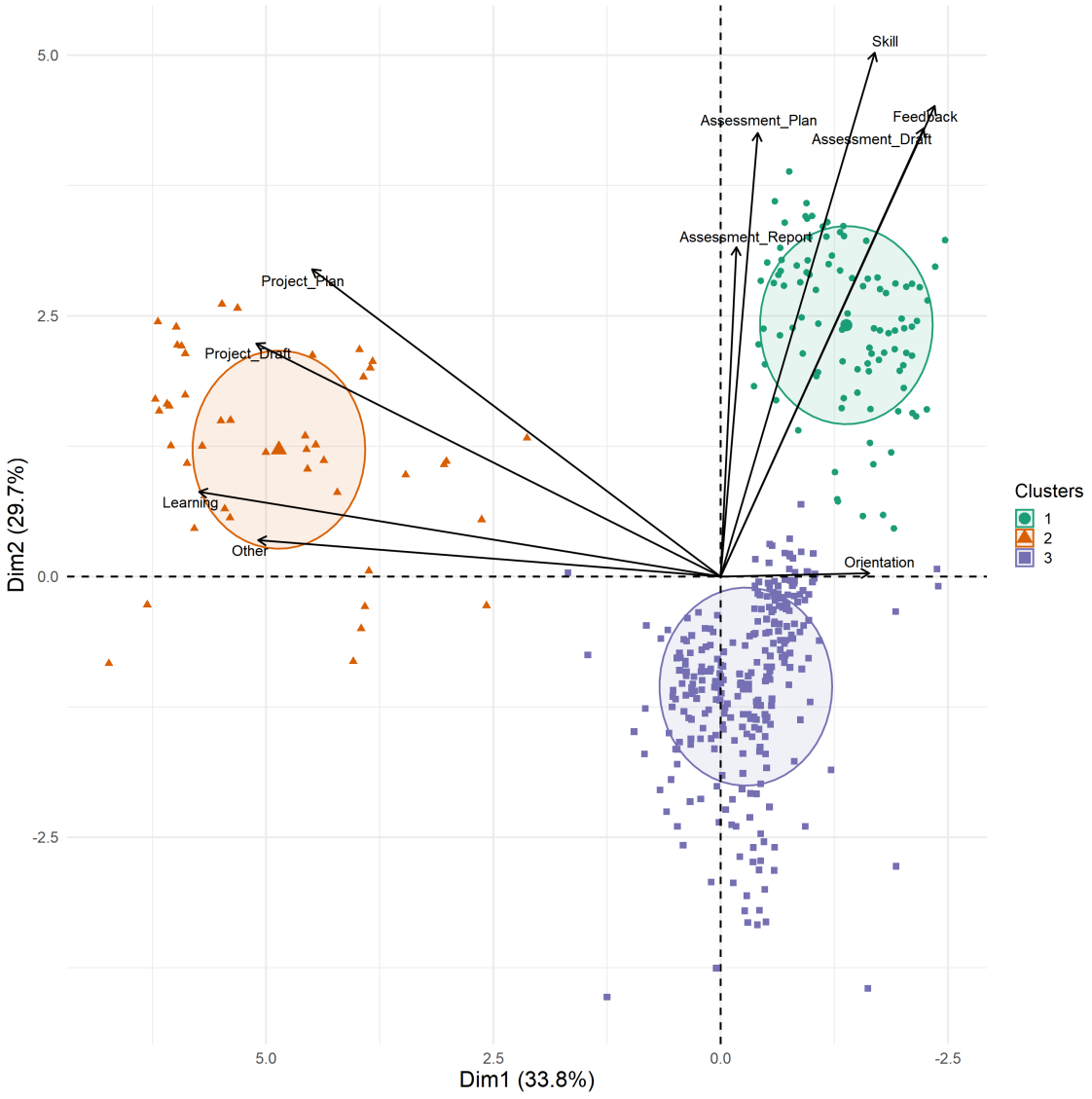


FIGURE 5.3: Visualising the activity types of team clusters with principal component analysis (PCA) biplot

The K-means clustering is used on the team engagement data described in Table 5.1 to identify the emerging patterns of team behaviour. The silhouette method returned a three-cluster solution as optimal, with maximised silhouette coefficient of 0.40. Therefore, three clusters were selected for the analysis, and it has been used in the rest of the analysis. The two-dimensions visual representation of three clusters is shown in Figure 5.3, using PCA to summarise the clustering space. The

three clusters are well-separated, with the first two principal components (on the X and Y axes) explaining 30% and 34% of variance, respectively. From the direction and length of the arrows assigned to each variable, the first principal component mainly captures activities related to project plan, project draft, learning, orientation and other activities. The first principal component mainly differentiates between cluster 2 on one side and the other two clusters on the other side. Similarly, the second principal component captures activities related to skill, feedback, and assessment, differentiating moderately between all three clusters, with cluster 3 having the lowest scores, cluster 1 having the highest, and cluster 2 being in the middle (see Figure 5.3).

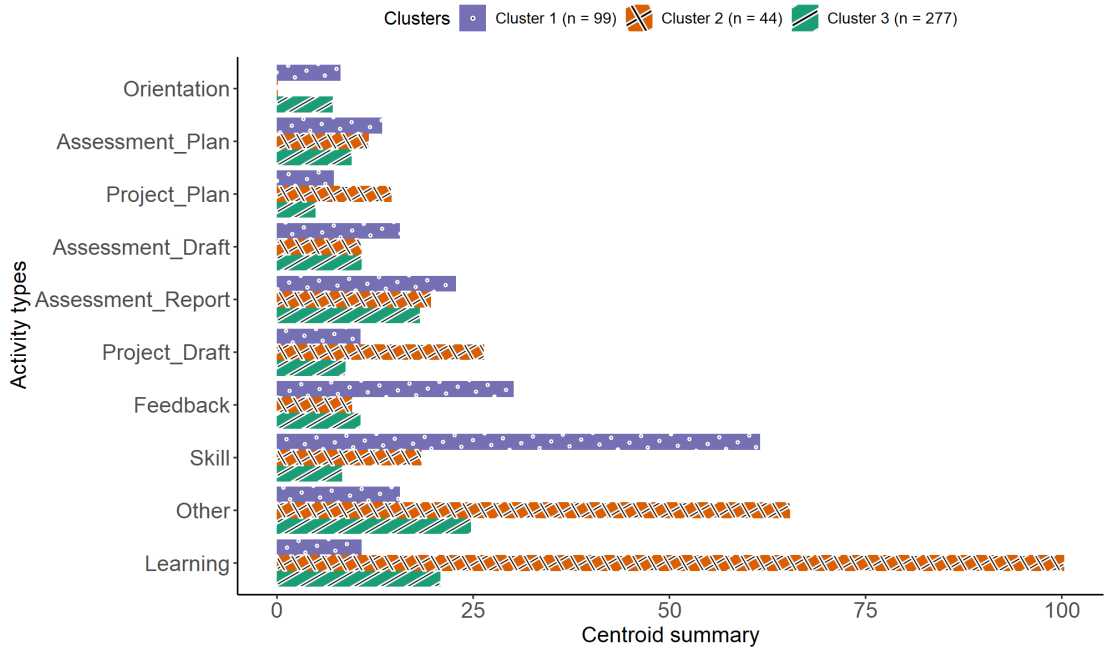


FIGURE 5.4: The centroids of the three clusters of emerging team behaviour.

As the next step of the analysis, centroids are examined for all three clusters (Figure. 5.4), looking at the values for each activity type. Teams in cluster 1 ($n = 99$) have high interactions with assessments, feedback and skill activities and the least with orientation. Teams in cluster 2 ($n = 44$) are the smallest clusters with high interactions with learning, other and project activities and have the least interactions with feedback and assessment activities. Teams in cluster 3 ($n = 277$) are the largest clusters with general interactions across all learning activities. The overall results highlight that certain clusters undertake particular learning

strategies that are either general (i.e., cluster 3), project orientated (i.e., cluster 2) or assessment orientated (i.e., cluster 1).

3

RQ2: Association of team behaviour with team performance

TABLE 5.2: The mean summary of the performance scores across each project and team size for each cluster

Team Cluster	Average team size	Project plan score	Project draft score	Project report score	Aveage score
Cluster 1	5.17	0.77	0.67	0.78	0.74
Cluster 2	4.66	0.67	0.55	0.55	0.59
Cluster 3	5.08	0.47	0.63	0.67	0.59

Given the observed differences in the emerging team behaviour, the next step in the analysis was to examine the association of team clusters with the teams' performance. Table 5.2 shows the scores for the three components of the project (i.e., plan, draft, and report), as well as their overall scores. Each score is in 0.00–1.00 range, where [0.00–0.24] indicates very poor performance, [0.25–0.49] indicates poor performance, [0.50-0.74] indicates average performance, and [0.75-1.00] indicates excellent performance. While the team size for each cluster was approximately five members, there were substantial differences in the team's scores. The teams in cluster 1 had the highest overall performance score, followed by the teams in clusters 2 and 3, which had the lowest overall score, mainly due to the significantly lower score for project plan (team cluster 2) and project draft and report (team cluster 3). Although, the scores for individual project component was very different for cluster 2 and 3. The performance of cluster 2 dropped over time, while cluster 3 was steadily improving. Kruskal-Wallis test (Kruskal & Wallis, 1952) is used with cluster membership as the independent variable and overall score as the dependent variable to examine the statistical significance of the observed performance differences. Kruskal-Wallis results show statistically significant differences

between clusters of teams and the overall score, $\chi^2(2, N = 420) = 92.9$, $p < 0.01$. The size effects for the differences between team cluster overall scores have a large magnitude where the effect size = 0.218.

The Dunn test (Dinno, 2015) is performed for each pair of clusters to further investigate the groupwise difference in their overall scores. Table 5.3 below shows the post hoc analysis results with the p-values adjusted using the Bonferroni technique. All three clusters had significantly different scores, except for clusters 2 and 3, where the difference was insignificant.

TABLE 5.3: Post hoc analysis between clusters and the mean summary of the performance score for the projects using the DunnTest with Bonferroni correction

Team Cluster Pair	Z	p
Clusters 1–2	5.30	0.000*
Clusters 1–3	9.60	0.000*
Clusters 2–3	1.00	0.316

RQ3: Association of team behaviour with temporal network motifs

Finally, the differences between team clusters regarding the temporal network motifs observed during their interactions in the learning platform are examined. Figure 5.5 shows the total number of motif instances for each of the five groups of temporal motifs. The most frequent motifs were Dyadic motifs, followed by Star Triadic, Switch Triadic, Ordered Triadic and Chaotic Triadic motifs. The results reveal that teams mostly form dyadic interactions in pairs, where two out of three team members interact with learning resources. There are strong triadic star interactions, where interactions with a learning resource of two team members follow interactions with the same resource by a third team member. Similarly, There is strong triadic switch interactions, where interactions of a single team member with learning resources were followed by interactions of two other team members (whose interactions do not follow each other's). In contrast, triadic interactions

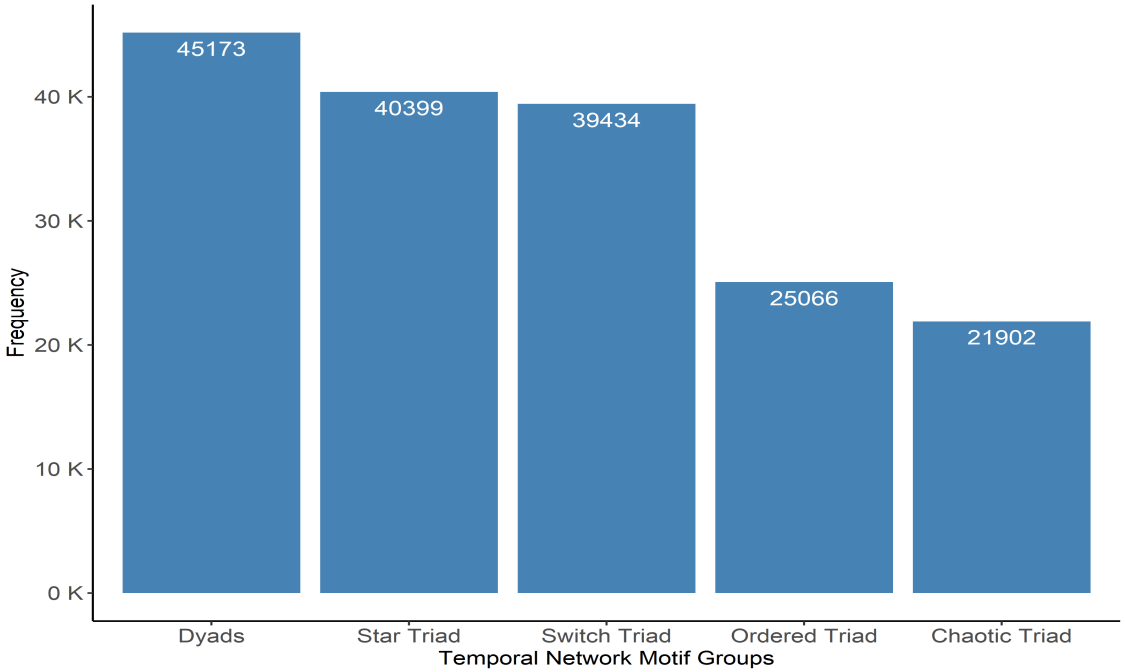


FIGURE 5.5: Total summary of the grouped temporal motif counts

where all three members have interacted with learning resources together in a sequential (ordered) and non-sequential (chaotic) occurs to a lesser extent than in the other motif groups'.

After examining the overall distribution of temporal network motifs, their distribution for each cluster was individually investigated. Figure 5.6 shows the normalised distribution of the five temporal motif groups for each team cluster, with some interesting differences between the clusters. Looking at the dyadic motifs, cluster 1 had much lower normalised values than clusters 2 and 3. In contrast, there is a more similar pattern for star triadic motifs, with clusters 1 and 3 having the highest normalised values and the lowest for cluster 2. There is a similar pattern for switch triadic motifs, with the highest normalised values for clusters 1 and 3 and the lowest for cluster 2. There is a different pattern, with cluster 1 having the highest normalised values, closely followed by cluster 3, while cluster 2 had significantly lower values than the other three clusters. Finally, cluster 1 has considerably higher normalised values for chaotic triadic motifs than the other clusters, followed by clusters 2 and 3 with relatively similar values.

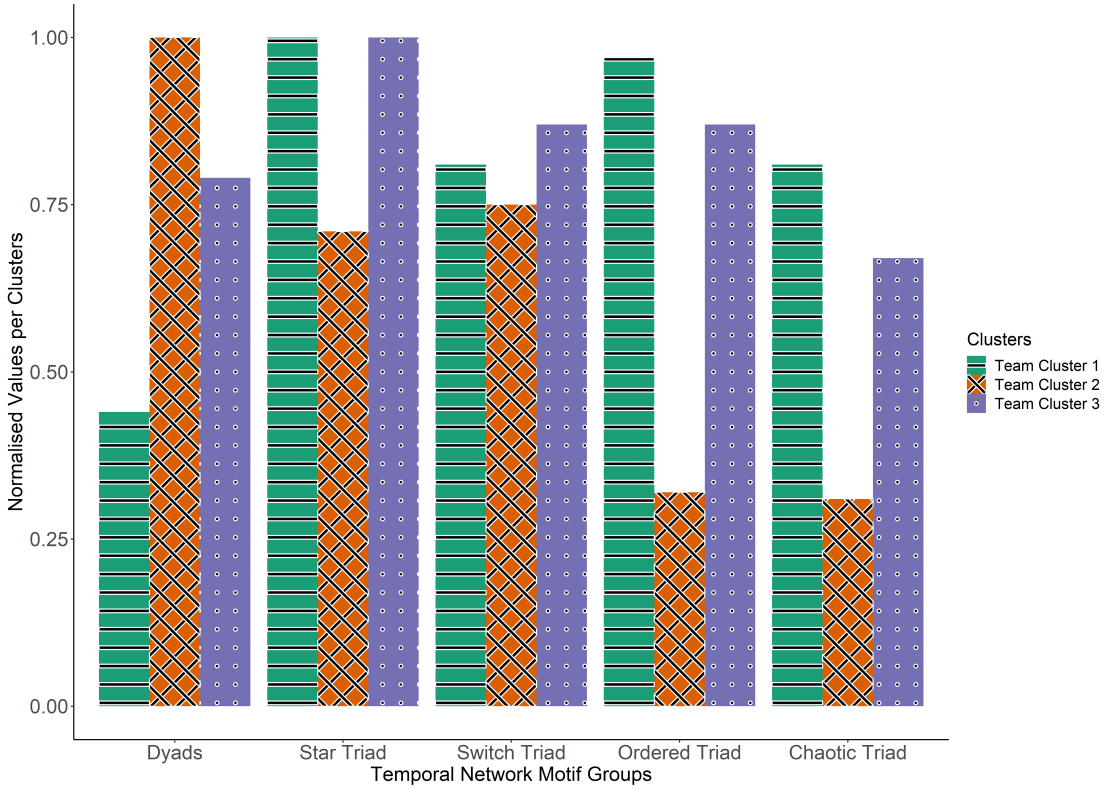


FIGURE 5.6: Normalised distribution of temporal network motif groups for each team cluster

Five Kruskal-Wallis tests are used (Kruskal & Wallis, 1952), with cluster assignment as the single independent variable and the frequencies of five temporal network motif groups as the dependent variables as seen in Table 5.4. The technique is used to further investigate the differences in temporal network motifs between the three clusters of teams.

TABLE 5.4: Kruskal-Wallis test between the team clusters and each motif group with their size effects

Comparison	*DF*	*N*	χ^2	*p*	*Effect size*	*Magnitude (as per Cohen, 1988)*
Dyads	2	418	20.58	0.000*	0.048	small
Chaotic Triad	2	418	31.47	0.000*	0.071	moderate
Star Triad	2	418	33.90	0.000*	0.769	moderate
Switch Triad	2	418	21.77	0.000*	0.076	small
Ordered Triad	2	418	24.35	0.000*	0.053	small

The results in Table 5.4 show significant differences between each team cluster and

each motif group. Moreover, it shows the reported size effects where chaotic triad and star triad have moderate magnitudes, while dyads, switch triad and ordered triad have small magnitudes. To further investigate the groupwise difference in the temporal motif instances, the Dunn test as a post hoc analysis is used after the Kruskal-Wallis test (Dinno, 2015). Table 5.5 below shows the results of the post hoc analysis.

TABLE 5.5: Post hoc analysis between clusters and the normalised number of the five grouped temporal motif instances using the DunnTest with Bonferroni correction showing Bonferroni adjusted p-values

Evo group comparison	Dyads	Chaotic Triad	Star Triad	Switch Triad	Ordered Triad
Clusters 1–2	0.000*	0.000*	0.027*	0.469*	0.000*
Clusters 1–3	0.149	0.000*	0.000*	0.000*	0.005*
Clusters 2–3	0.000*	0.036*	0.599	0.257	0.051

Table 5.5 compares each team cluster to determine differences between the five temporal motif groups based on Figure 5.6 results. The results have shown that most team clusters differ significantly based on their motif group characterisation. These results suggest that each team cluster has specific temporal motifs groups that indicate a team's performance.

RQ4: Changes in temporal network motifs over time

The final results reveal how temporal network motif groups change in frequency over an accumulative time for each cluster. These motif groups will provide insights into the cohesion of team members and how they interact based on their learning resources. Figure 5.7 shows the proportion of instances over three weeks that compromise each team cluster's five motif groups. The X-axis represents the day of the program, and the Y-axis represents the total number of instances for the categorised motif groups for each cluster. The legend labels correspond with the shape and colour of the line groups.

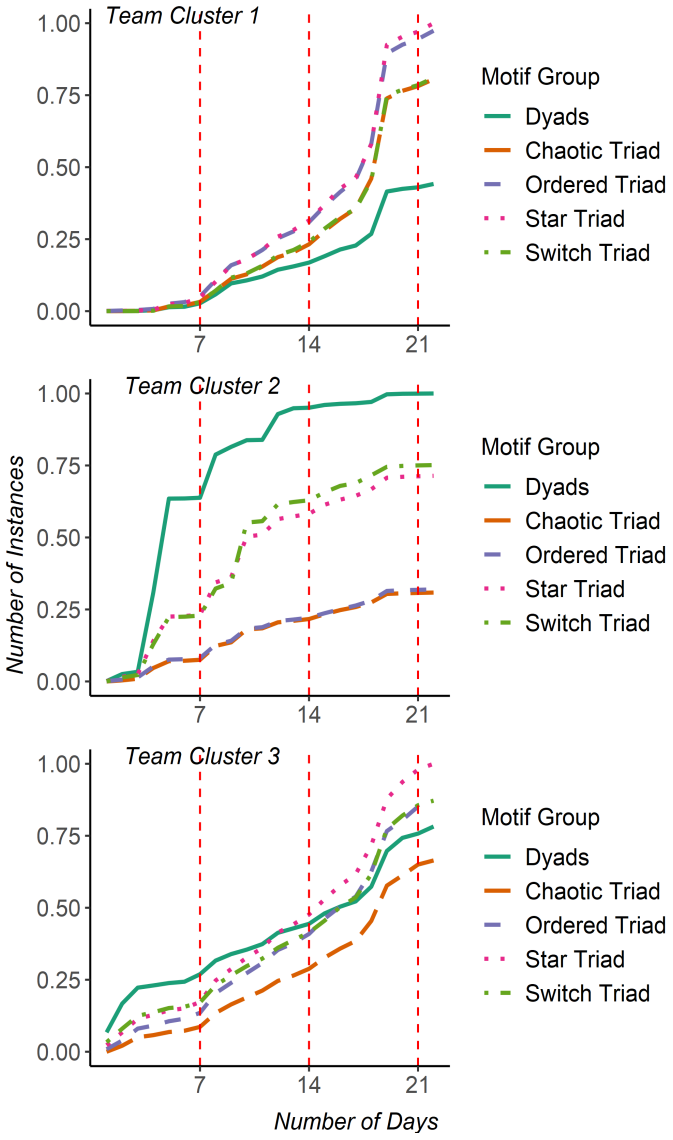


FIGURE 5.7: Overview of the portion of instances (normalised) over 3 weeks (21 days) for each motif group per team cluster.

Teams in cluster 1 show low temporal motif instances for the first week, where the distribution is mainly plateaued with most motifs. However, the rate gradually increases until the start of week two, where there is an increased spike of instances resembling more ordered triad and star triad based motif groups taking hold, closely followed by the switch triad and chaotic triad. An interesting observation is how the gaps between the triadic interactions substantially increase (spike) in distances from the dyadic interactions later in week three, indicating a consolidated team effort to complete their learning goals. The development of dyadic interactions for team cluster 1 is the lowest of the motifs groups. Cluster 1

is characterised by its triadic behaviours when interacting with learning resources more so than dyadic interactions, indicating a strong shared commitment with team members throughout their studies.

Teams in cluster 2 show many dyadic motif instances in the first week. These interactions spike in mid-week one and maintain dominance throughout the three weeks. The star and switch motif groups linearly increase as steps until the mid-second week when the slopes start to plateau. The chaotic and ordered motif groups are notably minimal compared to the development of other motifs, such as dyads. Cluster 2 is characterised by its dyadic behaviours when interacting with learning resources, more so than triadic interactions. Interestingly, cluster 2 plateaus on all motif groups around week two, suggesting limited shared commitment among team members.

Teams in cluster 3 show an early and modest increase compared to other team clusters in the first week for all motif groups, emphasising dyadic interactions within the team. By the first week, there is an interesting change where all triadic related motif groups start catching up and later become dominant in week three. The exception to this rule is the chaotic triads, which start closely shadowing the dyadic interactions by the end of week two. Teams way that temporal motifs develop for cluster 3 indicates a sense of teams developing common ground and eventually working towards a shared level of commitment among their team members near the end of their studies.

5.5 Discussion

RQ1: Emergent team behaviours

In this study, the emerging behaviours of teams were examined based on their engagement with online learning content and clustered them. The analysis revealed the resulting three clusters of teams with an average size of five members, each with very interesting distinct patterns of behaviour. Teams in cluster 1, representing

one-quarter of teams in WIL environments, tend to engage with content related to assessments, skills and feedback. These findings suggest that teams in cluster 1 are focused on activity content to maximise the outcomes of their assessments, paying particular attention to the feedback they receive and the skills to successfully achieve them. Existing studies seem to agree that these are the behaviours of learners who want to selectively maximise the completion of learning outcomes with minimal effort (Duff et al., 2020; Gasevic et al., 2017). Teams in cluster 2, representing one-tenth of learners, are characterised by their high engagement with projects, learning and other activity content while avoiding activities related to orientation. The teams are highly engaged and focused on maximising learning material to achieve their goals (Duff et al., 2020). Finally, teams in cluster 3, representing three-quarters of teams, have surface-level engagement compared to the other cluster teams. Their engagement tends to be lower but evenly spread across all activities. Similar studies with concurring learning behaviours indicate that these teams are moderately engaged (Barthakur et al., 2021).

RQ2: Association of team clusters with performance

The next findings reveal how the emergent team behaviours for each team cluster based on their engagement with learning activities are associated with their performance. Teams in cluster 1 achieve high and relative performance outcomes for all three assessments. These findings are not unexpected, as teams who seek frequent feedback from their industry supervisors are likely to achieve higher performance outcomes (Gabelica et al., 2012). Moreover, learners who practice engagement as opposed to learners who read learning content, are likely to lead to better outcomes, also known as the 'doers effect' (Koedinger et al., 2016). These findings might also explain the poorer performance outcomes from teams in clusters 2 and 3 based on their lower engagement with feedback and practical assessments. Interestingly, these two team clusters share almost identical performance outcomes with a key defining difference: how their performance outcomes develop. As such, teams in cluster 3 linearly increase their outcomes for each subsequent assessment,

whereas teams in cluster 2 linearly decrease their outcomes in each subsequent assessment. Even though teams in clusters 2 and 3 share identical performances, it can be argued that teams in cluster 3 contain motivated and keen learners to improve their learning (Zamecnik et al., 2022a). These are intriguing findings as their high engagement, especially for cluster 2, seems to suggest contradictory findings regarding the notion of high engagement leading to better outcomes (Lee, 2014; Papamitsiou & Economides, 2014). It is possible that in the context of team learning, there are more factors, such as the effectiveness of their cohesion (Bell et al., 2012).

RQ3: Team behaviours and their cohesion

Team behaviours and performance outcomes go hand-in-hand with their cohesion. Previous research is almost conclusive about the importance of task cohesion as a predictor of team success due to its nominal representation of performance based on behavioural interactions between team members (Grossman et al., 2021; Marks et al., 2001). Cohesion is often examined through the lens of engagement, including behaviours, such as on-task actions (Slavin et al., 2003). Although, very few studies have explored task cohesion through the lens of engagement and how it develops over time in collaborative learning (Zamecnik et al., 2022c).

The five motif groups based on the findings (i.e., Dyads, Chaotic Triad, Ordered Triad, Switch Triad and Star Triad) show exciting results in characterising each team cluster. For instance, teams that focus early on developing triadic (rather than dyadic) interactions generally achieve higher learning outcomes. This is aligned with previous research that shows the positive benefits of triadic interactions, in contrast to dyadic interactions, as the former (triadic) adopts more coherent learning behaviours and the latter (dyadic) forms more randomised learning behaviours (Harada, 2021). Triadic interactions form the basis of uniformity, emergent norms and cohesion by generating behavioural convergences (Simmel, 1950). Studies have found that dyadic interactions with interpersonal perceptions (LeDoux et al., 2012), dominating behaviours (Gommans et al., 2015), different

skillsets, individualistic backgrounds and inequity issues Popov et al., 2014; Shah and Lewis, 2019 can be detrimental to the formation of stable cohesion and collaborative learning. The literature corroborates with the results in this study to suggest that the "effectiveness of shared commitment" or types of "learning interactions" is a potential cause for lower team performance (i.e. teams in cluster 2). As a result, predominant dyadic interactions may be more harmful to the team's learning, particularly if team members have divergent behaviours (Popov et al., 2014), as opposed to triadic interactions, where team members have more converging behaviours and higher cohesion (Simmel, 1950; Yoon et al., 2013). Although, that is not to say that dyadic interactions should not occur in learning, as these risks can be mediated by pairing members with awareness of their knowledge distribution that closely resembles symmetrical ones than asymmetrical ones (Kozlov & Große, 2016).

The findings further show that each team cluster has distinctive triadic interactions. Teams with chaotic and ordered interactions seem to help characterise the clusters more than switch and star motifs. Given that the former pair has more edges between the nodes than the latter pair, thus more converging learning interactions among team members. Nevertheless, these triadic types provide interesting nuances in the learning processes of collaborative teams where there is limited research (Lämsä et al., 2021). The analysis of different types of triadic interactions have been conducted in education for discourse analysis (Chen et al., 2022b), but to the best of my knowledge, nobody examined motifs through a learner's cognitive actions. These results shed new light on the cohesiveness of team interactions with their learning resources.

RQ4: Temporal development of cohesion

Most studies analysed cohesion at one or two timepoints, and the results provide insights into cohesion development over time. Temporal motifs in this study have provided a clearer picture of how interactions take place over time. The finding

demonstrates the importance of measuring team learning dynamics as an emergent state that develops over time rather than a static behaviour (Santoro et al., 2015).

The results from our study provide interesting insights into the temporal nature of cohesion development. For instance, there is a big difference between teams in cluster 2 and cluster 3, despite teams in both clusters having similar final performances. Teams in cluster 2 have developed strong dyadic interactions early on. In contrast, triadic interactions have been far less common and only started to develop halfway through the course, suggesting lower levels of team cohesion. Interestingly, the performance of teams in cluster 2 has been steadily decreasing, likely linked to the very nature of their team interactions. Teams in cluster 3 performance are steadily increasing, suggesting that teams are learning individually at first while normalising their group behaviours and developing cohesion (Kozlowski et al., 1999; Mcgrath, 1991; Tuckman & Jensen, 1977), which may be consequential for their low performance outcomes in their first week. As teams in cluster 3 establish common ground by week two, their triadic interactions become more prevalent, resulting in increasing higher performance outcomes. Team cluster 3 can ultimately be characterised as a steady group that improves their performance and cohesion over time (Kozlowski et al., 1999; Mcgrath, 1991). Unexpectedly, teams in clusters 1 and 3 have similar interactions, where triadic interactions are more frequent than dyadic interactions. Nevertheless, clusters 1 and 3 have significantly different performance outcomes, where teams in cluster 1 are outperforming. A possible explanation can be the distance between triadic and dyadic motifs, where teams in cluster 1 are greater by threefold, indicating higher cohesive teams. However, further research is needed to examine the effects of temporal changes in group cohesion on learner performance in teamwork.

The characteristics of teams in cluster 1 are the most intriguing, as their learning behaviours, performance and interactions over time suggest that this team are the most cohesive compared to other teams. Future research needs to examine a ground truth to further substantiate the claim. This might be problematic in large online environments, where substantial surveys and interviews are not as practical to assess cohesion over time (Visser et al., 2000; Wright, 2005). Therefore, the

continuation of analytics-based measures to understand teams in these contexts is of the utmost importance and how developers can build online environments that capture characteristics of group dynamics (Gasevic et al., 2017; Santoro et al., 2015).

5.6 Limitation of the study

There are several limitations of this study. First, the data were used from a single platform, so interactions between learners (particularly face-to-face) might not be included, negatively affecting the study findings. Second, the selection of analysis, such as clustering techniques and the type of log data, can affect the identification of emergent behaviours. While the analysis strived to be comprehensive and used the silhouette method to identify stable clustering solutions, certain indicators of emergent behaviours might not be included. Finally, the generalisability of the results is limited by the focus on engagement behaviours from log data based on team interactions with their learning resources, as opposed to the social interaction between team members as a measure of cohesion, which was not available for this study. In future studies, incorporating the social dimension will draw relationships with the task dimension to represent team cohesion. Capturing social and task aspects will allow a richer understanding of how emerging behaviours are characterised.

5.7 Implications

This study was motivated to examine team cohesion primarily through their synchronous interactions using temporal network motifs. The exploratory study provides insights into the distinguished team clusters with their emerging learning behaviours, performance associations and cohesion in an online learning platform at scale. These findings using LA can help instructors monitor and support a

team's cohesion over time by examining the way temporal motifs occur in a collaborative context. The innovative findings in this study can be one way to improve the health of team dynamics in online collaborative learning environments. Given that instructors have very limited options to understand team dynamics over time, it places teams at risk with team members that may be social loafers or have commitment issues in completing their tasks (Kerr & Bruun, 1983; Latané et al., 1979). Teams may require pedagogical support to nudge their behaviour to establish common grounds in these circumstances. Such that instructors can promote teams by encouraging them to be collaborative and seek out learning materials together instead of relying upon other members to do the work for them. Moreover, temporal network motifs may offer a new avenue to understand learners' engagement beyond summarisations. As seen in the findings, the motifs provided a way to understand how members interacted with their learning resources throughout their study. Similar LA approaches could help further understand challenging collaborative processes to monitor and examine in collaborative learning environments (Haataja et al., 2018; Lämsä et al., 2021; Zamecnik et al., 2022c).

The novel analytics-based measure has direct and practical implications for measuring cohesion as a proxy for learning interactions. To apply the approach, the minimal data required from the LMS event log (i.e., TML environments such as sensors or computing devices that involve learning) needs to have three columns, each with populated instances. Namely, the user column, the activity column and a timestamp column. The user column requires a minimum of two users per team or group. The activity column can have any amount of categories or be filtered based on specific interactions that the user requires. Finally, the timestamp column needs to contain information similar to the ISO 8601 standard, which represents dates and times in a standardised format. A condition that needs to be met is that the user (i.e., group or team member) interacts with their activity and is recorded as an instance. The description of the type of activity can be brief. The data can then be transformed into a one-mode network where all nodes are connected to each other based on a single type of relationship using programming languages such as Python or R. The data format will have a source node (a user),

target node (a user) and timestamp (in seconds) in .txt format. Each row instance is based on the type of activity that occurred in a timestamp. The data then is then used for input for the SNAP graphical library in C++ or Python (Leskovec & Sosič, 2016) that provides a count of the 36 temporal motif occurrences using the algorithm by (Paranjape et al., 2017), describing it in further detail. Additional modifications can be done to the library by changing the code and adjusting the output as necessary. For instance, counting the occurrences of temporal motifs per hour, day, week or month. Moreover, separating the temporal motif counts by activity type or anything that is required by the user. Follow-up analysis can be undertaken if required using the data output from the SNAP library to other software for analysis.

Temporal motifs can be used to measure cohesion in teams by identifying patterns of interactions among groups or team members over time. For instance, assessing the strengths of the connections between members, the degree of coordination or cooperation in their actions and the types of motifs that occur. Moreover, using the properties of motifs to identify specific factors that contribute to or detract from cohesion within the group. Further research work is required to comprehensively understand reasonable proxies of cohesion when using temporal motifs. Overall, the properties of temporal motifs provide a powerful tool for understanding the dynamics of cohesion and how it develops over time.

5.8 Concluding remarks

The static measurements and analysis of cohesion within teams in learning environments through cross-sectional studies using surveys have been repeatedly examined (Salas et al., 2015). However, literature in TML environments where team cohesion was measured and analysed using trace data from platforms is scarce. This chapter presents a novel study that addresses the stated gap by employing an analytics-based measure for cohesion to understand the group synchrony

of learning interactions in clustered teams. The main findings arising from this chapter reveals:

- Distinctive relationships between teams and their level of group synchrony, learning engagement and performance outcomes.
- Team interactions with learning resources using temporal network motifs can help proximate the emergence of cohesion.
- The analytics-based measures can be generalisable across most collaborative LMS showing teams interacting with learning resources.
- A relationship between existing literature on the synchronous interactions of team learning and cohesion, adding credence to the measurement.

The chapter addresses research aim two by providing an analytics-based measure to analyse cohesion over time in TML environments. The promising approach has substantial implications and generalisability for measuring cohesion indicators using log data collected from LMS. The findings of this study provide instructors with a way to monitor the cohesion of student teams while they are working on group learning activities. These results must be reproduced to indicate generalisability in such contexts. There is a need to ensure construct validity by drawing upon methods that have been carefully developed based on relevant existing knowledge to strengthen the novel approach explored in this chapter. In the next chapter, cohesion-based surveys will be utilised with temporal network motifs to determine the extent of the generalisability. There is also a further need to understand how learning constructs, such as engagement, performance and feedback, can characterise team cohesion and temporal network motifs over time. Characterising team cohesion based on their learning constructs will allow educational stakeholders to distinguish vulnerable teams that require group support. These concerns are addressed above in the subsequent study in Chapter 6.

Chapter 6

The evolution of cohesive perception in teams and their learning constructs

This chapter introduces a novel approach to characterise cohesive perceptions in a collaborative environment through the team's learning constructs, such as engagement, performance, group synchrony, and feedback. This work addresses research aim three and expands on the previous chapter regarding the characterisation of cohesion using group synchrony as a proxy. With the need to monitor team cohesion in TML, it is important to understand how cohesive perceptions can change in these environments. The study utilises a mixed-method approach and explores how these learning constructs characterise teams with similar or different cohesive perceptions.

6.1 Introduction

The third research aim explores the team's cohesive perceptions regarding how similar or different their agreement or disagreement is. The outcome of the research aim will address the gaps in characterising their perceptions over time with their

learning constructs. This Chapter presents the results and discussion of team perceptions and how to prompt behavioural changes that aid in team cohesion and learning. As a result, the study explores the differences between the start and end of the course in terms of task cohesion scores and changes in the team's cohesive perceptions. It also examines the differences between the start and end of the course in terms of overall learning engagement, performance, and synchronicity. Lastly, it investigates the types of feedback teams receive at the start and end of the course based on their level of cohesive perception.

Section 2.3 in Chapter 3 contains extensive literature that motivates the research questions in this Chapter. The study builds on previous work in Chapter 5 by utilising the developed analytics-based measure given the promising applications, while incorporating a standardised survey to measure the task cohesion of teams to help establish further generalisability. The explorative study also addresses how team cohesive perceptions are characterised by their learning constructs to inform an understanding of team dynamics that occur in TML from this Chapter.

The methodology uses a combination of data science techniques, such as temporal network motifs, ENA and summary statistics to concisely answer the research questions in this chapter. Summary statistics are used to explain and interpret the differences between a team's task cohesive score with their two cohesive perceptions that can be similar or different. A combination of summary statistics and temporal network motifs are used to characterise the two cohesive perceptions and how it evolves over time. Lastly, ENA is used to help identify connections between the type of feedback and the cohesive perceptions of the teams.

The chapter is organised as follows: Section 6.1 provides an overview of the problem and highlights the limitations of existing work in collaborative learning. Section 6.2 highlights the research questions, while Section 6.3 provides information on the study participation, design and data analysis. Section 6.4 shows the results of the team's cohesive perception, evolutions, and connections to task cohesion

and learning constructs. Sections 6.5, 6.6, and 6.7 provide interpretations, limitations, and implications, respectively. This chapter is concluded in Section 6.8 with a study summary.

The study explores team cohesion and their perceptions in an online environment. Teams with similar cohesive perceptions have higher task cohesion, performance, and well-rounded provisional feedback, while teams with different perceptions have lower task cohesion, performance, and feedback. Analytics-based measures using temporal network motifs can characterise cohesive teams. Teams with higher frequencies of triadic motifs indicate stronger cohesion. Similar results were found in Chapter 5. The study emphasises the importance of supporting vulnerable teams in collaborative learning based on their cohesive perceptions and task cohesion. The research provides a way for educational stakeholders to measure and analyse the cohesion of teams in collaborative TML contexts.

6.2 Research questions

In this chapter, the task cohesion scores are explored and how learning constructs such as engagement and performance align with teams in agreement and disagreement to understand their behaviour. The team's cohesion based on their learning resource interactions is considered. The type of feedback given to teams is measured and analysed as to how they can support behavioural changes in teams to improve their cohesion. These effects are captured at the beginning and end of their course to understand the changes. As a result, the three following questions are addressed:

- RQ1: What are the differences between the start and end of the course with regard to task cohesion scores and the changes in the team's cohesive perceptions?
- RQ2: What are the differences between the start and end of the course with regard to overall learning engagement, performance and synchronicity?

- RQ3: Depending on the level of cohesive perception, what types of feedback do teams receive at the start and the end of their course?

6.3 Methodology

This section describes the research methodology used to investigate the research questions, including the research design, data collection methods, and data analysis procedures.

6.3.1 Study design

The study looked at learners who participated in a voluntary work-integrated learning (WIL) program facilitated by a major educational provider to develop their employability skills through team projects, coaching and professional development. The WIL environment provides opportunities for learners to apply their academic knowledge to practice by closely working with mentors and clients from the industry (Patrick et al., 2008). Learners are placed into teams and must strategise and work together by interacting with their learning resources and completing their projects. The practical skills learners gain from the WIL experience can be translated back to their studies and enhance their learning (Cooper et al., 2010b).

The cohorts covered in this analysis are from late 2021 and early 2022, consisting of 944 learners divided into 194 teams across 15 sessions of the same program involving work on a real-world project. Teams were formed randomly and were expected to collaborate daily by engaging with learning materials to complete their project. Details about the learner's demographics, such as age and gender, are confidential and therefore, not recorded. Each week, the students were expected to produce one deliverable: project plan in week one, project draft in week two, and finally, project report in week three. The instructors consist of academic mentors and industry clients. Using a specific list of criteria, the instructors rated each deliverable on a range within the 0.00-1.00 scale and provided detailed written feedback

to students. During the three-week program, teams interact with various activity types on the WIL platform where each team member's interaction is recorded through log data. The descriptions of activity types are found in Table 6.1 below.

TABLE 6.1: Overview of the engagement activity types and descriptions

Activity type	Description
Orientation	Activities which introduce the program to students and welcome the students or give them an overview
Learning	Activities which are related to students learning or teaching course contents to students
Skills	Activities which are related to skill development, such as best practices in collaboration
Feedback	Activities which are related to feedback, such as client and mentor comments.
Project Draft	Activities which are related to drafting project, such as content related to drafting
Project Plan	Activities which are related to planning project, such as content related to planning
Assessment Draft	Activities which are related to submission of the draft for assessment
Assessment Plan	Activities which are related to the submission of the plan for assessment
Assessment Report	Activities which are related to the submission of the final report for assessment
Others	Other activities within the system apart from all above, such as registration, etc

To examine the evolution of team cohesion and overall learning constructs in a collaborative learning environment, the data is analysed and collected from the technology provider from their most populator offering. Table 6.1 shows the activity type categories and their descriptions of course materials that teams interact with weekly. These extracted engagement metrics were categorised according to the program design of the major educational provider. For example, the Skills activity type is categorised based on the associated description outlined in the table (e.g., "Team professional development", "Conflict resolution", "Networking"). The project and Assessment activity types represent specific activities, where the former is based on course material that aids learning, and the latter leads to the submission of the project.

The provider conducted surveys at the end of week one (Mid test) and week three (Post test) to examine collaboration, ethics, privacy, teamwork and team cohesion. The questionnaires were conducted to gather insights into optimising resources to improve courses and provide pedagogical support for teams by the provider. For the thesis, the focus is on the responses collected for task cohesion (i.e., a dimension of team cohesion), where team members are provided with four questions. There are typically several items involved in task cohesion questionnaires in contemporary research. Although, there are restrictions on the number of questions the educational provider can share with team members related to space. Therefore, four questions from the survey have been carefully modified to capture the meaningful aspects of task cohesion without losing relevance. The task cohesion survey is closely based on Carless (2000) measurement of cohesion in work teams. Teams responded using a 5-point Likert scale (1: strongly disagree, 5: strongly agree). The four questions used in this study are as follows:

- Commitment: "I am happy with my team's level of commitment and contribution".
- Resolve: "If conflicts arose, we were able to resolve them within our team".
- Receptive: "Our team was receptive to feedback and took action".
- United: "Our team was united in trying to reach the team's goals and outcomes for this program".

Mentors and clients provide feedback to each team for each deliverable. Given the richness and abundant feedback given to teams, they have been coded according to the feedback model by Hattie and Timperley's (2007). The feedback analysis involved splitting the feedback from paragraphs into sentences and labelling them into codes, which created 5,730 rows. To label the feedback data, two coders processed the first 200 rows with an agreement of 77%. The next 300 rows yielded a 75% agreement rate between the two coders. The disagreements arising from the remaining 25% were resolved by the two coders coming to a final agreement

on the label. The remaining 5,230 labels were split into two for each coder (i.e. 2,615) to label the rest of the data. To mitigate uncertainty when labelling the remaining rows, the coder highlighted them, and a mediator was introduced to help determine the final label.

TABLE 6.2: Overview of Hattie and Timperley's (2007) feedback model and coded examples in this study

Feedback code	Feedback type	Description	Feedback examples
FT	Feedback on task	Feedback on how well tasks are performed	*"Whilst a useful start, the limitations of the survey size and demographic should have been covered."*
FP	Feedback on process	Feedback on the learning processes underlining or relating and extending tasks	*"The tasks are being evenly distributed across the team and the research requirements being spread across the weeks, keeping it realistic in the given timeframe."*
FR	Feedback on regulation	Feedback on how students monitor, direct and regulate their own learning	*"How will you know if you have completed the tasks successfully?"*
FS	Feedback on self	Personal evaluation and affect (usually positive) about the student)	*"Overall, exceptional work."*

In Table 6.2, the Feedback type column shows the type of feedback given, and the Description column explains the description of each code row by row. The Feedback examples column is one excerpt of the feedback given to teams in this study. In addition, the additional code: "G" is included, which represents comments given to teams that are 'General' but are part of the team's feedback (e.g., "I hope that makes sense, but we can chat in our meeting").

6.3.2 Data analysis

The first step was examining the internal consistency of the surveys to identify the degree to which the items on a survey measure the same construct or concept using Cronbach's alpha reliability coefficient. The cohesion perceptions of teams are then calculated by looking at similarities of members' responses to four cohesion survey questions based on Equation 6.1.

$$P_i = \frac{1}{n(n-1)} \left\{ \left(\sum_{j=1}^{k} n_{ij}^{2} \right) - (n) \right\} * 1/STDEV \tag{6.1}$$

Equation 6.1 shows a modified inter-rater agreement (IRR) equation based on weighted Fleiss' Kappa (1971) in combination with Kendall's rank correlation to provide a more comprehensive assessment of IRR (Kendall, 1938). The i is the question item, n is the team size, k is the rating scale and n_{ij} is the j_{th} rating of question item i. Combining Fleiss' weighted kappa with Kendall's rank correlation provides a more comprehensive assessment of inter-rater reliability when there are many raters and multiple categories.

The purpose of using the modified IRR equation is to account for 3 or more coders to ensure the viability of the measurement by evaluating both the level of agreement among raters and the consistency of their rankings. It calculates how many team members selected the same choice per question. A measure above 0.33 indicates agreement among the raters (i.e., cohesive perceptions are similar). If below 0.33, the agreement among the raters is poor (i.e., cohesive perceptions differ). Let there be three hypothetical scenarios for how team members rate: 1) if all four members choose the same rating, then the weighted kappa would be 1, which indicates perfect similarity in the team; 2) if three out of four members choose to give the same rating and one member chooses a different rating, then the weighted kappa would be 0.40, indicating similar perceptions of team cohesiveness; 3) if all four members choose a different rating from each other, then the weighted kappa would be 0.00, indicating no agreement upon teams cohesiveness. Given that team members must respond to four questions, a final step is conducted to

determine if the overall team's cohesive perceptions are similar or different using a majority rules formula. For instance, if team members' ratings agree on three out of four questions, this signals similar perceptions of team cohesiveness. Moreover, if peers agree or disagree with two of the four items, the team members do not have a common perception of their team's cohesiveness.

Box plots are used to visually show the distribution of data and their means to gain insights into the results. They are also used to compare the relationship between a team's cohesive perception of the Mid and Post Test with their task cohesion scores. Flowcharts are used to illustrate the extent of the evolution and the associated raw numbers in tables for the analysis of team changes from the Mid to the Post Test. The analysis and data visualisation were performed in R programming language.

The next stage of the analysis involved characterising the evolution of team cohesion by their performance and engagement. Firstly, the performance scores are analysed to interpret how well teams perform, including their performance score changes between week one (Mid Test) and week three (Post Test). The next step includes testing for significance in performance from the Mid to the Post Test and a follow-up post hoc analysis using DunnTest with Bonferroni correction. The second part involves collecting click data based on team interaction with the WIL platform. The raw logs are collected and pre-processed to be more fine-grained using learning analytics approaches, such as categorising the extracted data metrics as outlined in Table 6.1. Analysing fine-grained data in learning analytics research has continuously shown support for making inferences about academic performance and self-regulated learning (Hadwin et al., 2007; Winne, 2020). Therefore, trace data is drawn to understand how these interactions corroborate with the evolution of a team's cohesion and perform a non-parametric significance test and post hoc analysis using DunnTest with Bonferroni correction.

Dynamic interactions are characteristics of cohesion that emerge in teams. Therefore, temporal network motifs were a promising choice to investigate teams in agreement and disagreement at the beginning and end of their course. Examining

how motifs develop over time when teams interact with learning reasons will help characterise the teams. As such, certain attributes of motifs will help identify teams that are performers or at risk. This approach aims to observe if previous findings of motifs in Chapter 5 that depict teams in higher cohesion corroborate with the findings in this study.

The connection between feedback codes and each group of team perception applied the epistemic network analysis (ENA), a method for quantifying links among coded data in a dynamic network model (Shaffer & Ruis, 2017). ENA is used to identify patterns of association, structures and strengths in a complex network over time (Shaffer et al., 2009). A network projection is created for each group of team perception to understand connections with the feedback types they receive. One approach commonly applied in ENA is to show the salient differences between networks by subtracting each connection's weights, as done by Tsai and colleagues (Tsai et al., 2021) study. Subtracting the networks helps to illustrate what co-occurrences of the feedback types are stronger based on the edge thickness and node size. The differences in the networks are then compared along both X-axis (SVD1) and Y-axis (SVD2) using Mann-Whitney's non-parametric test with a threshold of 0.05 and their size effect. Finally, to effectively visualise the differences between the groups, the means in the network were rotated to position group means on the X-axis.

The final part also investigates the differences in feedback provision by clients and mentors to teams. The purpose of the analysis is to understand what type of feedback is provided by clients and mentors using Timperleys and Hatties (2007) coding scheme. These impacts on teams are not extensively explored in collaborative learning literature, and there is merit in investigating how feedback is provided that may impact their learning. For the remainder of this paper, the teams in agreement and disagreement as 'team states' to describe the two groups are conceptualised.

6.4 Results

6.4.1 Task cohesion, cohesive perceptions and their evolutions

TABLE 6.3: Cronbach alpha reliability coefficient

Survey	Items	Alpha
Pre-test	4	0.93
Post-test	4	0.94

The first part of the analysis involved measuring the internal consistency and reliability of the four pre-test and post-test survey items using Cronbach's alpha (Cronbach, 1951). In Table 6.3, the reported alpha estimates exceed reliability ($\alpha = 0.70$) (Nunnally, 1978). The high reported results of alpha 0.93 (pre-test) and 0.94 (post-test) are expected, as the items in the survey are of similar context but not redundant.

TABLE 6.4: Horn's Parallel Analysis for factor retention using the mean estimate

Survey	Factor	Adjusted eigenvalue	Unadjusted eigenvalue	Estimated bias
Pre-test	1	3.09	3.16	0.07
Pre-test	2	-0.05	-0.03	-0.02
Post-test	1	3.18	3.25	0.07
Post-test	2	-0.04	-0.02	0.02

Table 6.4 shows the factor loadings results for the Mid and Post-test of the survey using Horn's Parallel Analysis (Horn, 1965). Results suggest that the adjusted eigenvalues > 0 indicate dimensions to retain. Therefore, only 1-factor loading can be considered for the four questions in the Mid and post-test. In that sense, the items in the survey are closely related. These corroborate with the reported high alpha readings shown in Table 6.3, showing item similarity.

Several observations of the shape and position of the grouped box plots in Figure 6.1 differ between the cohesive perceptions. The box plots for teams with similar cohesive perceptions are short and small, suggesting that team members

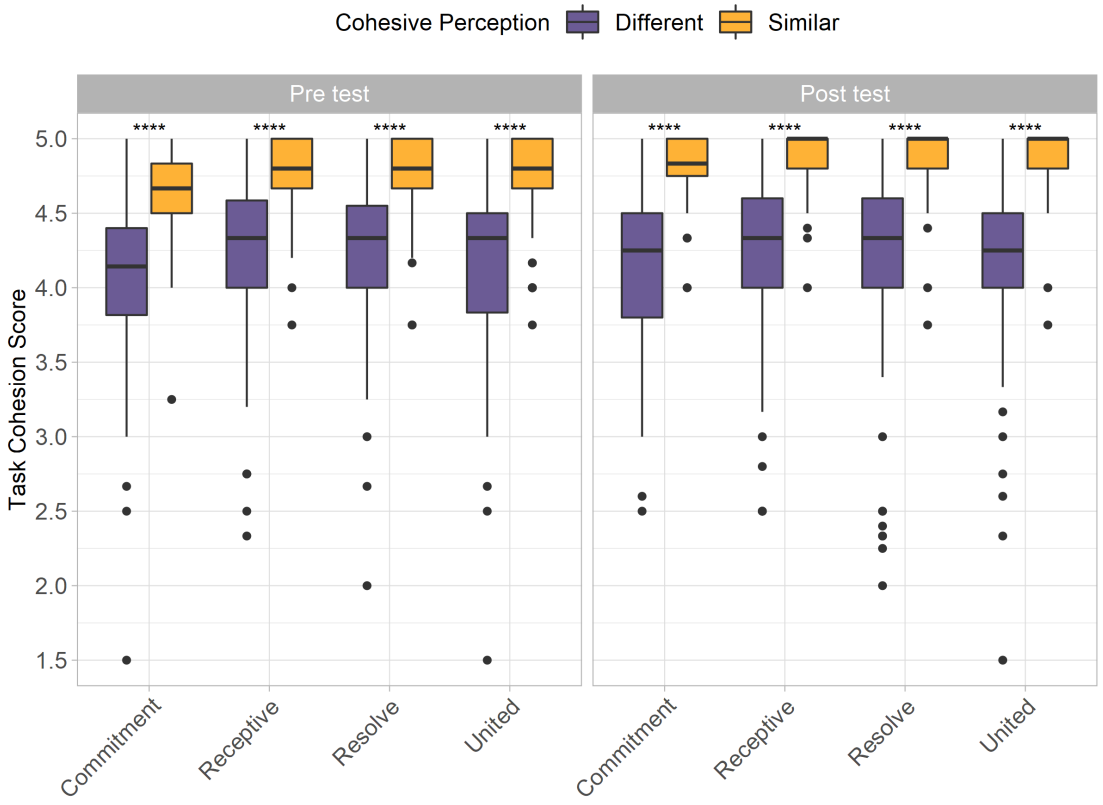


FIGURE 6.1: Box plot of task cohesion scores along the Y-axis and the four items along the X-axis and the comparison between pre-test and post-test of Cohesive Perception that are Similar and Different.

consistently rated consistent task cohesion scores. The box plots for teams with different cohesive perceptions are long, suggesting that team members do not rate task cohesion scores similarly. Team members with similar cohesive perceptions have fewer outliers and some variability from the mean in terms of how they rate the task cohesion scores of their team. Team members with different cohesive perceptions have more frequent outliers and variability from the mean in terms of how they rate the task cohesion scores of their team. There are differences between the cohesive perceptions, where teams with similar perceptions have higher task cohesion scores and teams with different perceptions have lower task cohesion scores. As a result, a non-parametric test using Kruskal-Wallis was performed to test significant differences between the cohesive perceptions for each item (Kruskal & Wallis, 1952). Significant differences exist in all scenarios with notated p values < 0.0001 above each box plot grouping, with their respective survey items. The results indicate that task cohesion scores are higher for teams with similar cohesive

perceptions and lower for teams with differences.

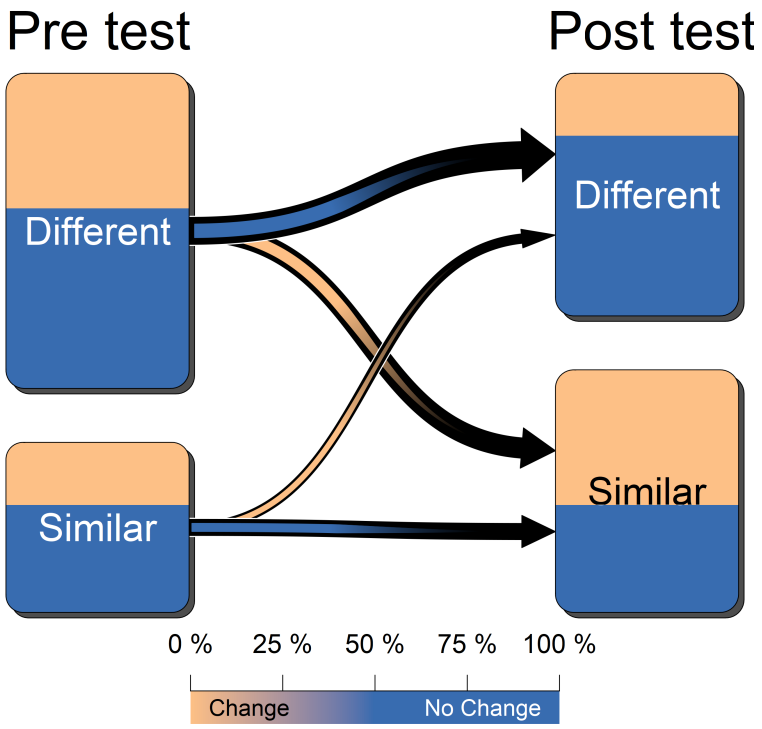


FIGURE 6.2: Evolution plot showing how team's cohesive perceptions that are Similar and Different in the pre-test change and flow to the post-test.

Figure 6.2 shows how teams change between cohesive perceptions from the pre-test (week one) to the post-test (week three). The directed arrows show the number of teams changing (blue) and not changing (gold) states. Results show 126 teams with different perceptions of the pre-test and 68 with similar perceptions. In the post-test, the teams are equally distributed with regards to their cohesive perceptions (i.e., 97). By the post-test, there is an increase of 29 additional teams obtained similar cohesiveness perceptions, as shown in Table 6.5. The results indicate that most team cohesive perceptions are different at the beginning of their program. By the last week of their program, team cohesive perceptions become increasingly similar. In that sense, cohesive perceptions of teams reach an even split between similarities and differences.

Table 6.6 shows the number of teams that had different evolutionary trajectories over the course duration. No change group includes teams whose perceptions of team cohesion did not change between the pre-test and post-test. In contrast,

TABLE 6.5: The counts of how many teams change between Similar and Different cohesive perceptions from the Pre-test to the Post-test based on Figure 6.2

Cohesive Perceptions	Pre-test	Post-test	Difference
Similar	68	97	+29
Different	126	97	-29

the change group contains teams whose perceptions did change. There are four different Evolution groups, as a result of their evolution type, where the Evolution group column and codes 1, 2, 3 and 4 represent cohesive perceptions that are; 1) similar and have no change in evolution; 2) different and no change in evolution; 3) similar and change in evolution and; 4) different and change in evolution, respectively. There is, on average, a team size of 5 members for each Evolution group, indicating comparable team sizes.

TABLE 6.6: The counts of how the teams cohesive perceptions evolved between similar and different from the Pre-test to the Post-test based on Figure 6.2

Evolution group	Cohesive perceptions	Evolution	Evolution count	Average team size
Group 1	Similar	No change	43	5.23
Group 2	Different	No change	72	4.74
Group 3	Similar	Change	25	5.22
Group 4	Different	Change	54	5.39

6.4.2 Cohesive perceptions and evolutions with performance, engagement and group synchrony

Performance

The Evolution group column is the naming convention used to further describe the cohesive perceptions and evolution in Table 6.7. Table 6.7 shows each evolution group's performance score for their three main assessment projects: Plan, Draft, and Report. The pre-test score column represents the assessment project score (i.e., Plan) from week one and the post-test score column represents the average assessment project score (i.e., Draft and Report) from weeks two and three. In that sense, the pre-test represents assessments after week one, and the post-test

represents assessments after weeks two and three. The Average score column shows the average scores between the Plan, Draft and Report assessments for each cohesive perception.

TABLE 6.7: The mean associated performance scores for each Evolution group between the Pre-test and Post-test

Evolution group	Cohesive perceptions	Evolution	Pre test		Post test	
			Mean	σ	Mean	σ
1	Similar	No change	0.84	0.22	0.89	0.09
2	Different	No change	0.84	0.17	0.77	0.18
3	Similar	Change	0.86	0.17	0.85	0.13
4	Different	Change	0.86	0.13	0.85	0.13

The performance scores for all four Evolution groups on the pre-test were approximately the same, indicating no differences between teams with different perceptions of team cohesion. However, the performance score results for the Evolution groups on the post-test are different, indicating a notable change in their performance. Evolution group 1 had similar starting perceptions and no change over time, with increasing scores from 0.84 to 0.89. Evolution group 2 had different starting perceptions and no change over time, with decreasing scores from 0.84 to 0.77. The results indicate that teams who maintain similar cohesive perceptions increase their performance, and teams who maintain different cohesive perceptions decreased their performance. For Evolution groups 3 and 4 that evolve (i.e., where cohesive perceptions change from similar to different and vice-versa), their performance scores remain close, ranging from 0.84 to 0.86 for the pre and post-test. As a follow-up analysis, the Kruskal-Wallis test was performed to examine the differences between four evolution groups with regard to their pre-test and post-test scores. The results for the Post score show significant differences between the Evolution groups (χ^2 (3, N= 194) = 26.472, p value $<$ 0.000), with a moderate magnitude (0.124). As a result, a post hoc analysis for the Post score was performed using the DunnTest with Bonferroni correction for the adjusted p value in Table 6.8.

Based on the post hoc analysis in Table 6.8, the comparison between groups 1 and 2 shows the adjusted p values and significance where p value $<$ 0.05 indicated with

TABLE 6.8: Post hoc analysis of the differences in assessment performance between four groups of teams based on their evolution of team cohesiveness

Evolution group comparison	Z score	adjusted p
Group 1–2	5.046	0.000*
Group 1–3	2.167	0.181
Group 1–4	-1.841	0.393
Group 2–3	2.172	0.179
Group 2–4	-2.936	0.020*
Group 3–4	-0.418	1.000

Note. * indicates statistical significance.

an asterisk for each row per group comparison. Comparison between group 1 and 2 indicates significance in performance. The significant difference between groups 1 and 2 indicates that teams with similar cohesive perceptions that do not change will have higher performance than teams with different cohesive perceptions that do not change. The results suggest that they will perform better if teams continue to have similar cohesive perceptions. Moreover, a comparison between Evolution groups 2 and 4 indicates significant differences in performance. The significant difference between evolution groups 2 and 4 suggests that teams starting with different team cohesion perceptions but converging to similar perceptions over time have higher performance than teams whose perceptions differ and do not change over time. The results suggest that teams will perform better if they converge to similar cohesive perceptions over time.

Engagement

The results from Table 6.9 show the average number of interactions for teams in four evolution groups, across different types of activities in the course. The pre-test represents the mean engagement for week 1.5, whereas the post-test represents the mean engagement for weeks 2 and 3. The Evolution groups have similar interactions across all N activity types, showing minor differences between the pre-test and post-test. Nevertheless, the non-parametric Kruskal-Wallis test was performed to check for significant differences between four evolution groups at the pre-test and post-test amongst the type of activities. All engagement activity

TABLE 6.9: The mean summary of team activity for each of the evolution groups during the three-week program

Pre-test									
Evolution group	Assess draft	Assess plan	Project plan	Orientation	Feedback	Learning	Other	Project draft	Skill
1	0.00	10.54	6.69	11.37	11.72	8.61	8.69	13.03	20.39
2	0.50	11.44	6.28	12.60	8.74	9.10	7.92	10.31	18.92
3	0.32	11.97	5.91	10.18	12.00	8.37	6.56	11.96	19.57
4	0.22	11.53	6.68	12.13	10.77	9.44	8.22	11.85	20.06
Post-test									
Evolution group	Assess draft	Assess plan	Project plan	Orientation	Feedback	Learning	Other	Project draft	Skill
1	15.85	12.11	2.96	6.73	35.95	9.11	6.03	16.18	48.68
2	15.68	12.15	2.78	5.98	28.44	12.87	10.46	16.77	49.97
3	15.76	12.41	3.06	2.36	35.73	12.36	12.32	17.06	49.16
4	16.05	12.10	3.49	8.61	34.75	11.46	8.84	15.66	51.17

types except the Feedback (χ^2 (3, N= 194) = 14.737, p value < 0.002) for the pre-test had a large magnitude (0.06) and Feedback (χ^2 (3, N= 194) = 13.671, p value < 0.003) for post-test had a small magnitude (0.056).

The only significant differences between the four evolution groups were observed for the feedback activity. The engagement with most other learning activities was not different between the Evolution groups. As a result, the post hoc analysis test was conducted with pairwise comparisons using Dunntest with Bonferroni correction to check between the Evolution groups to determine how the Feedback activity differs between each group:

TABLE 6.10: Post hoc analysis between Evolution groups and the mean summary of the Mid-Test and Post-Test regarding the Feedback activity feature with pairwise comparisons using DunnTest with Bonferroni correction

Evolution group comparison	Pre test		Post test	
	Z score	adjusted p	Z score	adjusted p
1–2	3.278	0.006*	2.898	0.022*
1–3	-0.034	1.000	-0.179	1.000
1–4	-2.758	0.034	-2.600	0.055
2–3	0.957	0.035*	0.237	1.000
2–4	-2.423	0.092	-2.832	0.027*
3–4	0.843	1.000	0.387	1.000

Note. * indicates statistical significance.

Table 6.10 shows the significant differences between evolution groups 1 and 2, and also between groups 2 and 3 for the pre-test. For the post-test, there are significant differences between Evolution groups 1–2 and 2–4. Teams with different cohesive perceptions have comparatively lower feedback interactions than teams with similar cohesion perceptions. Teams who are not cohesive throughout the three-week program have significantly lower interactions with feedback content than other Evolution groups.

Group synchrony

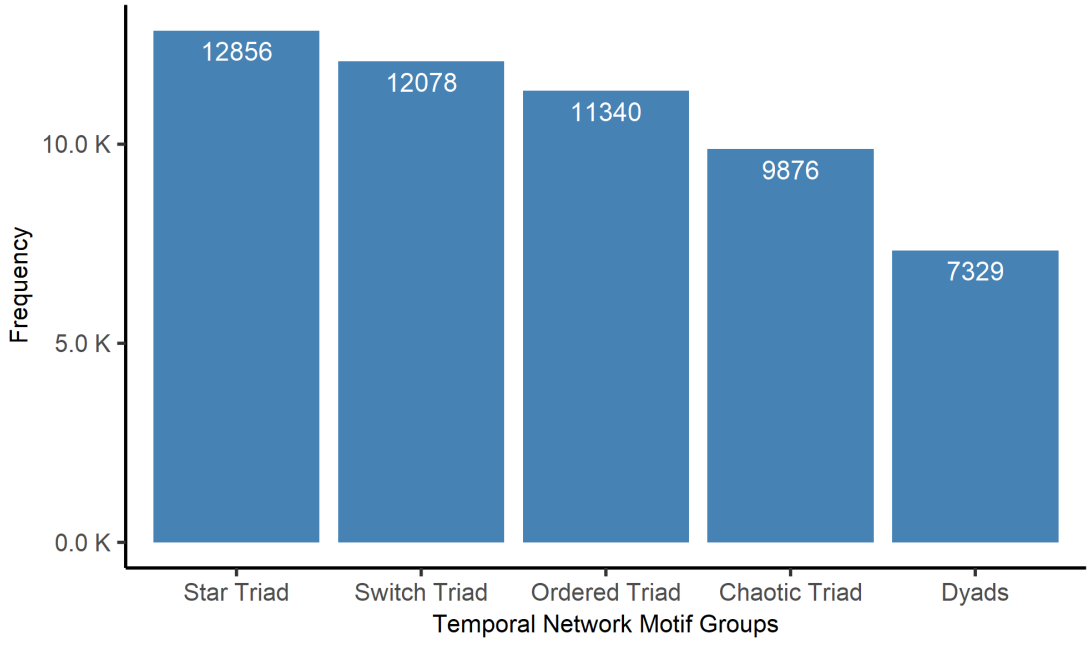


FIGURE 6.3: Total summary of the grouped temporal motif counts

The study examined the differences between the evolution groups regarding the development of temporal network motifs observed during their interactions in the learning platform. Figure 6.3 shows the total number of motifs for each of the five groups of temporal motifs. The most frequent motifs were star motifs, followed by the switch, ordered, chaotic and dyad motifs. The results reveal strong star triad interactions, where interactions with a learning resource of two team members follow interactions with the same resource by the third team member. Similarly, there are strong triadic switch interactions, where interactions of a single team

member with learning resources were followed by interactions of two other team members (whose interactions do not follow each other's). In contrast, triadic interactions where all three members have interacted with learning resources together in a sequential (ordered triad) and non-sequential (chaotic triad) occurs to a lesser extent than in the other motif groups. The dyads are the lowest occurring motif, where teams mostly form dyadic interactions in pairs, where two out of three team members interact with learning resources

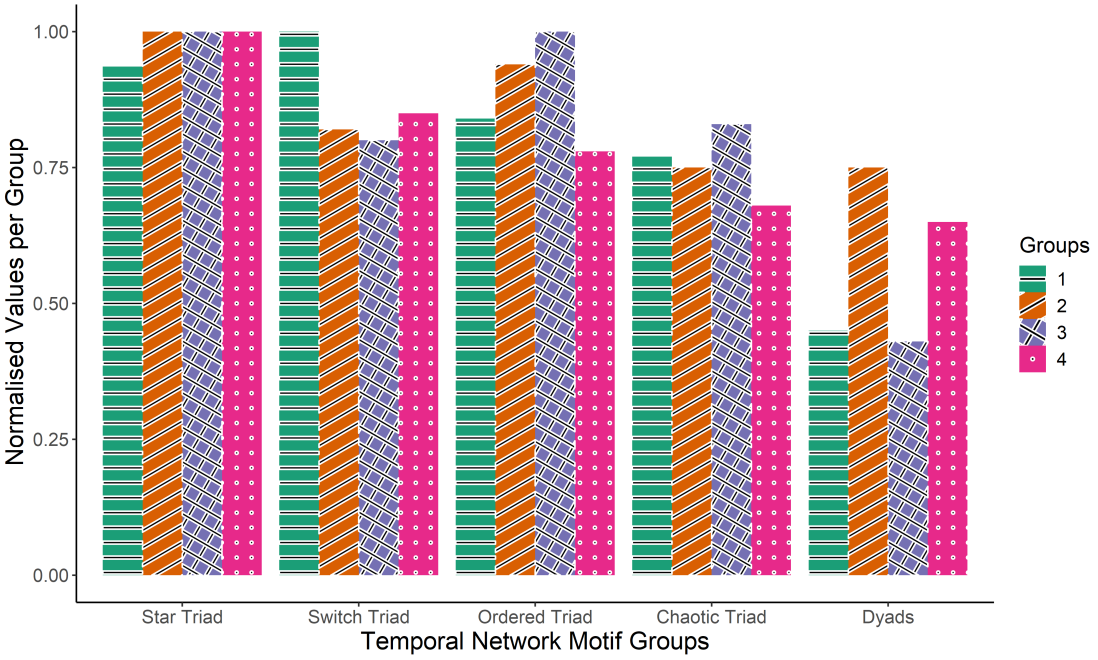


FIGURE 6.4: Normalised distribution of temporal network motif groups for each Evolution group

After examining the overall distribution of temporal network motifs, the distribution for each evolution group individually was investigated. Figure 6.4 shows the normalised distribution of the five temporal motif groups for each evolution group, with some interesting differences between them. Looking at the star triad motifs, each group had similar average normalised values. For switch triad motifs, only group 4 has the highest normalised values, whereas the other groups are around the same. A different pattern for the ordered triad motifs is observed, with groups 3 and 2 having the highest normalised values and groups 3 and 4 having the lowest. In contrast, for the chaotic triad motifs, groups 1 and 2 are similar and below groups 3 and above groups 4. Finally, clear differences for the dyadic motifs, with

groups 2 and 4 with the highest normalised motifs and the lowest for groups 1 and 2, were observed. To further investigate the differences in temporal network motifs between the four evolution groups, five Kruskal-Wallis test (Kruskal & Wallis, 1952) tests were used, one for each network motif group. The group assignment is the single independent variable, and the frequencies of five temporal network motif groups as the dependent variables as seen in Table 6.11.

TABLE 6.11: Kruskal-Wallis test between the team clusters and each motif group with their size effects

Comparison	*DF*	*N*	χ^2	*p*	*Effect size*	*Magnitude (as per Cohen, 1988)*
Dyads	3	194	17.447	0.000*	0.076	moderate
Chaotic Triad	3	194	13.217	0.004*	0.052	small
Star Triad	3	194	17.057	0.000*	0.072	moderate
Switch Triad	3	194	8.232	0.041*	0.027	small
Ordered Triad	3	194	9.897	0.019*	0.036	small

Note. * indicates statistical significance.

The results in Table 6.11 show significant differences between evolution groups for each motif group. The reported size effects are shown where dyads and star triads have moderate magnitudes, while chaotic, switch and ordered triads have small magnitudes. To further investigate the groupwise difference in the temporal motif instances, the Dunn test as a post hoc analysis was used after the Kruskal-Wallis test (Dinno, 2015). Table 6.12 below shows the results of the post hoc analysis.

TABLE 6.12: Post hoc analysis between clusters and the normalised number of the five grouped temporal motif instances using the DunnTest with Bonferroni correction showing Bonferroni adjusted *p* values

Evo group comparison	Dyads	Chaotic Triad	Star Triad	Switch Triad	Ordered Triad
1–2	0.010*	0.134	0.019*	0.159	0.234
1–3	1.000	1.000	1.000	1.000	1.000
1–4	0.005*	0.005*	0.036*	0.395	0.115
2–3	0.106	1.000	1.000	1.000	0.214
2–4	1.000	1.000	0.002*	0.192	1.000
3–4	0.045*	0.085	1.000	1.000	0.105

Note. * indicates statistical significance.

Table 6.12 shows the results of the comparison between four groups of teams to examine the differences with regards to five temporal network motifs based on Figure 6.4 results. The results have shown that several evolution groups differ significantly in terms of dyads, chaotic and star triad motifs. These suggest that the evolution groups have specific temporal motifs that indicate a team's performance.

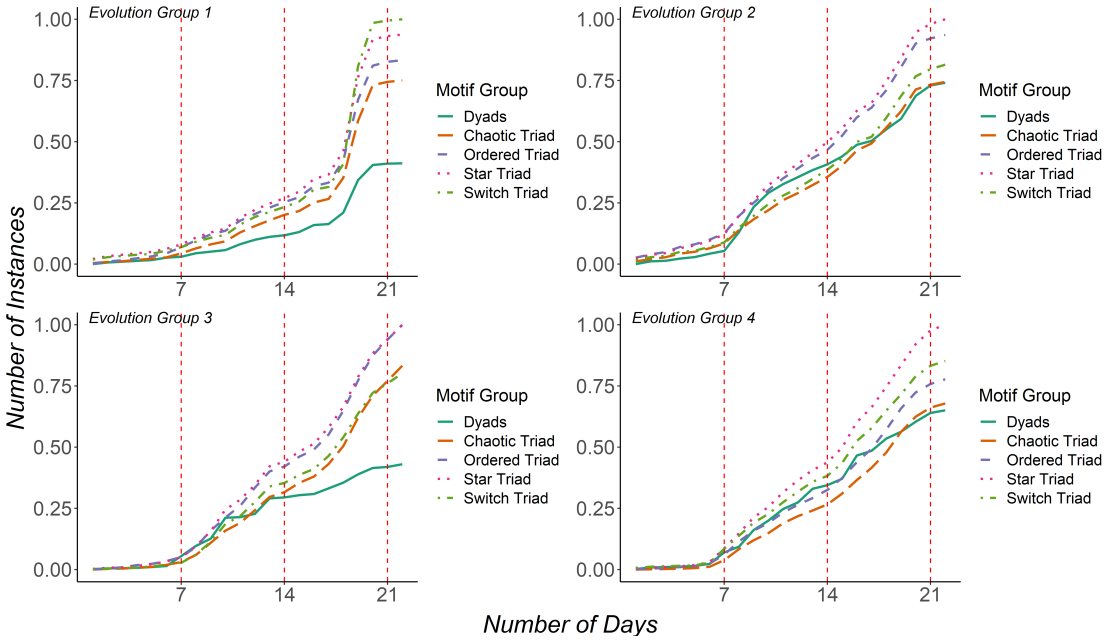


FIGURE 6.5: Overview of the portion of instances (normalised) over 3 weeks (21 days) for each motif group per Evolution Group.

The final results reveal how temporal network motif change in frequency over time for each evolution group. These motif groups will provide insights into the cohesion of team members and how they interact based on their learning resources. Figure 6.5 shows the proportion of instances over three weeks that compromise each evolution group's five motif groups. The X-axis represents the day of the program, and the Y-axis represents the total number of instances for the categorised motif groups for each evolution group. The legend labels correspond with the shape and colour of the line groups.

Teams in evolution group 1 show a low number of temporal motif instances for the first week, where the distribution mainly plateaued with most motifs. However, the rate gradually increased until the start of week two, where there was an increased spike of instances resembling more ordered switch and ordered triads based

motif groups taking hold, closely followed by the ordered triad and chaotic triad. An interesting observation is how the gaps between the triadic interactions substantially increase (spike) in distances from the dyadic interactions later in week three, indicating a consolidated team effort to complete their learning goals. The development of dyadic motif interactions for evolution group 1 is the lowest of the motifs groups. Evolution group 1 is characterised by their triadic behaviours when interacting with learning resources more so than dyadic interactions, indicating a strong shared commitment with team members throughout their studies.

Teams in evolution group 2 show an early and slight increase in motifs in week one compared to the groups, emphasising mostly ordered and star triads. Changes by week two are seen, where dyadic motifs rise above the other triadic motifs and persist until week three. In week three, the dyadic motifs start to fall and align with the chaotic triads, while ordered and star triads gradually rise. Interestingly, the motif groups overlap throughout the team's study. In contrast, evolution groups 1 and 3 are tightly triadic motifs distant from the dyadic interactions. The results for group 2 suggest that there might be limited shared commitment among team members.

Teams in evolution group 3 show a low number of temporal motif instances for the first week, where the distribution is mainly plateaued with most motifs, similar to evolution group 1. However, these interactions spike more prominently in group 3, with a tighter development of the five motifs and a fluctuating dyad motif. By week three, there is a gradual but sharp slope upwards, where the dyadic motifs start to fall rapidly behind the triadic motifs and plateau at the end of week three. Group 3 is characterised by its prominent triadic interactions, namely ordered, star, followed by the switch and chaotic triads.

Teams in evolution group 4 show almost no motif development in the first week, indicating a lack of collaboration among team members. Although, by the start of week two, these motifs develop and have similar patterns to group 2 until the end of week two. The dyadic motifs tend to be in the middle of the triadic interactions, with the chaotic and ordered triad being the lowest throughout week

two. The star triad motifs are dominant throughout the weeks, along with switch and ordered triads by week three. Interestingly, the dyadic motifs start to decrease in accumulative frequency during week three, while the chaotic triads eventually overtake the dyads. The findings may indicate a sense of teams developing common ground and eventually working towards a shared level of commitment among their team members near the end of their studies.

6.4.3 Cohesive perceptions and evolutions with feedback

To understand how four evolution groups differ with regard to received feedback, we used Epistemic Network Analysis (ENA). Using ENA, the co-occurrence of feedback was examined at the different levels (i.e., process, task, self and regulation) as it is being provided to the teams. The thicker lines indicate more frequent connections, and the thinner lines indicate less frequent connections. Nodes positioned closer suggest less variance between them than nodes (Shaffer & Ruis, 2017).

Figure 6.6 shows the comparative differences between evolution groups with the feedback they received from instructors over the three-week program. Figure 6.6-A reveals connections between Regulation, Task, Process and Self that are stronger with Similar → No change group in orange (evolution group 1), indicating well-rounded feedback. For Different → No change group in cyan (evolution group 2), the connections are stronger with Task and General, indicating limited feedback variability in comparison. Figure 6.6-B reveals stronger connections between General, Process and Task with Similar → Change group in green (evolution group 3). For Similar → No change group, connections are stronger with General, Self and Regulation. Teams who remain in a similar perception receive feedback related to team strategy and improvement of their work, as opposed to their Change perception from similar to different with a focus on general appraisal and team regulation. The results indicate that teams moving from a similar to a different perception may be indicative of internal behaviour and emotional issues that occur, which instructors try to mend. Figure 6.6-C reveals stronger connections between Self,

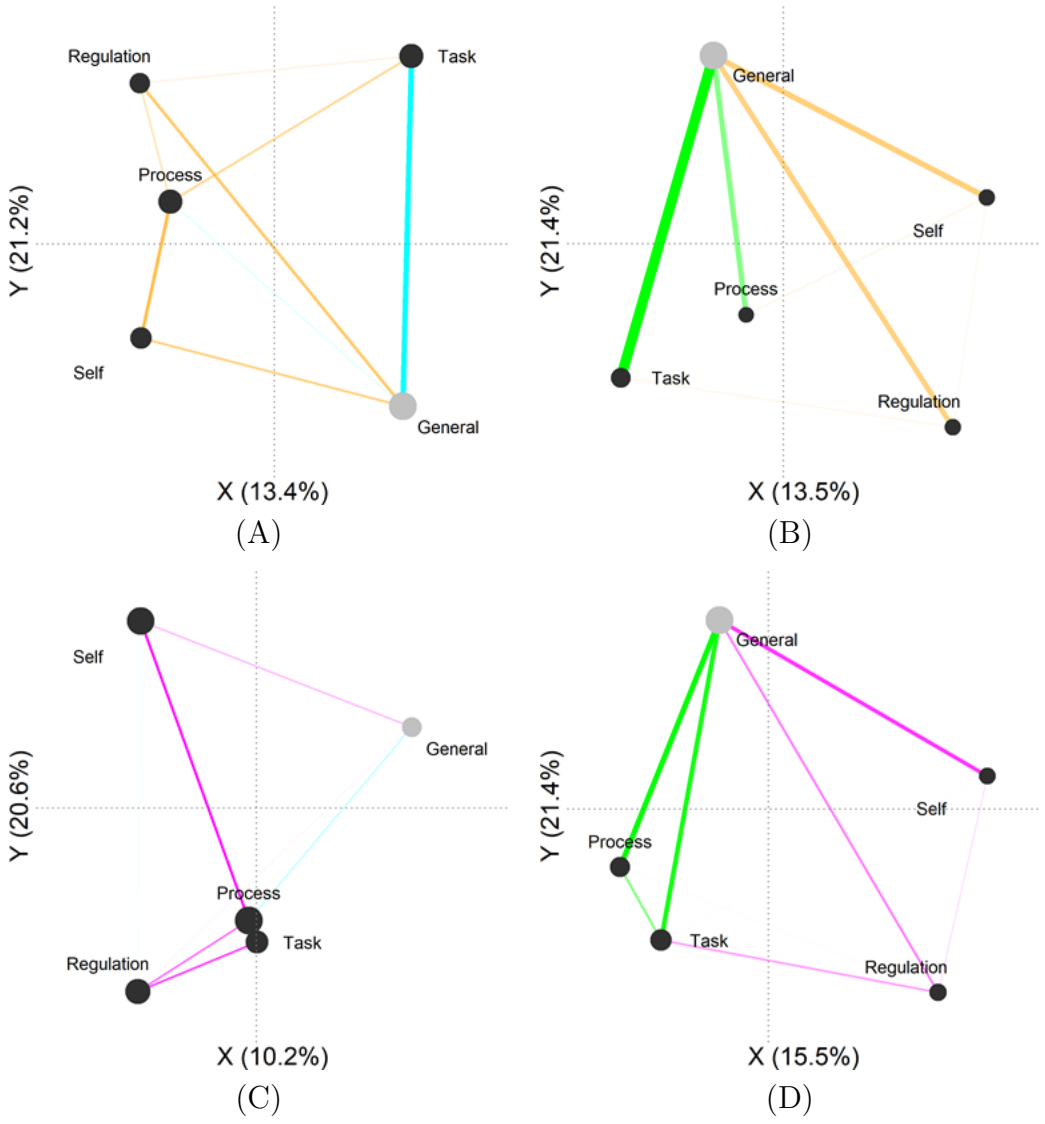


FIGURE 6.6: Subtracted feedback networks of the four evolution groups rotated by their respective means.

Process, Task and Regulation for Different → Change group in purple (evoluton group 4), whereas Different → No change group (cyan) shows stronger connections with General and Process. The results of teams shifting from different to similar may indicate their well-rounded feedback, as opposed to teams who stay different, which only show connections with general feedback and team strategies. Figure 6.6-D reveals stronger connections for General, Process and Task for Similar → Change group (green). Connections for General, Self, Regulation to Task, are stronger for Different → Change group (purple). The results indicate that the combination of regulation, self and task are the main factors for teams shifting

towards similar cohesive perceptions, as opposed to just task, process and general.

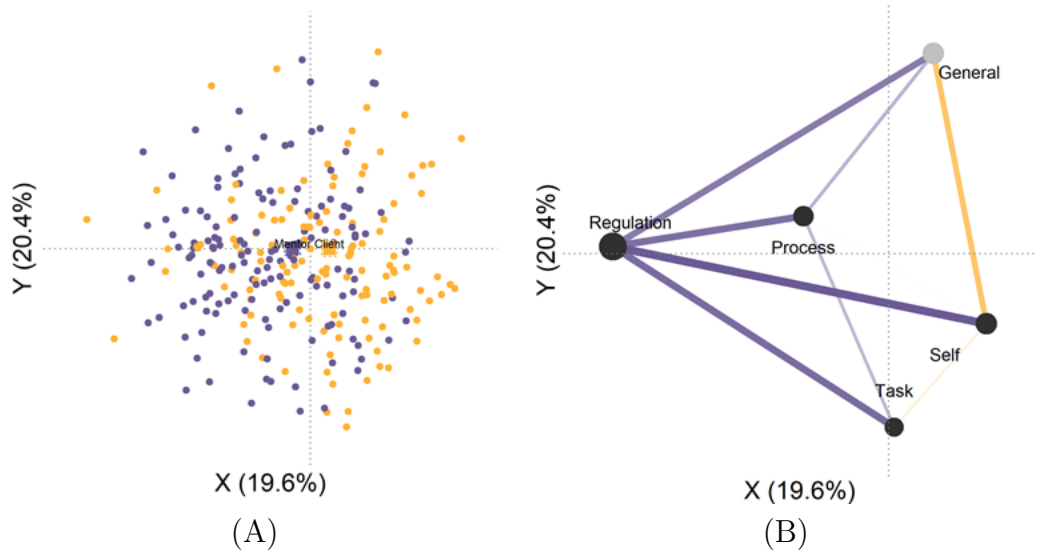


FIGURE 6.7: Shows the comparison of feedback connections between Client and Mentor. Mentors provide the most variance in feedback types: Regulation, General, Process, Task and Self.

The connections between feedback labels received by teams from clients and mentors were explored to understand how instructors provide feedback. In Figure 6.7-A, the left plot contains the instructor centroids from the first (purple) and second (gold) with the associated means and confidence intervals. The right plot in Figure 6.7-B contains the subtracted networks of instructor feedback (Mentor in purple, Client in gold), in which Mentor connections are subtracted from Client connections. Connections coloured purple are stronger in the Mentor feedback network, and connections coloured gold is stronger in the Client feedback network. The results reveal that Mentors provide more extensive feedback that is useful to teams, helps improves their work, facilitates strategies, provides appraisals and regulates behaviours or actions in teams more than the Client's feedback. The strong connections between General and Self feedback indicate that the Client provides feedback that does not focus on improving the team's learning. There is an indication that different instructors (i.e., Mentors or Clients) influence the team's cohesive perceptions based on their feedback.

Table 6.13 shows the significant differences between the evolution groups and their subtracted networks in Figs 3 using the Mann-Whitney test. The results show

TABLE 6.13: Mann-Whitney test is performed along the X-axis and Y-axis, showing significance (p) and size of effect (r) for each group comparison

ENA group comparison	X-axis		Y-axis	
	p value	size of effect (r)	p value	size of effect (r)
Fig 6.6A	0.00*	0.17	0.81	0.01
Fig 6.6B	0.02*	0.17	0.80	0.02
Fig 6.6C	0.14	0.08	0.98	0.00
Fig 6.6D	0.00*	0.26	0.75	0.02
Fig 6.7B	0.00*	0.28	0.37	0.04

Note. * indicates statistical significance.

significant differences along the X-axis that have moderate size effects. The results reveal that the substracted networks indicate substantial comparisons along the X-axis, except Figure 6.6-C.

6.5 Discussion

RQ1: Team cohesive perceptions and evolution

The analysis of evolution groups revealed insights about the team's cohesive perceptions and of evolutions over time. The insights show that teams who are not cohesive in week one have lower cohesion than cohesive teams. By week three, teams that are not cohesive have lower cohesive scores, whereas cohesive teams have increased their cohesive scores. The results are expected as teams with different cohesive perceptions risk lower cohesion and subsequent performance outcomes. Another insight is that most teams have different cohesive perceptions at the beginning of their program (week one) but later shift towards a similar cohesive perception, where teams have established common ground (Kozlowski & Klein, 2000). From a theoretical point of view on team dynamics, the results are not surprising as teams build relationships early on among their members, eventually leading to better cohesion (Kozlowski & Chao, 2012; Santoro et al., 2015). The insights from calculating the cohesive longitudinal perspective using the modified IRR formula show an early indication of teams fluctuating. In that sense, cohesion can increase and decrease over time, as it is not immutable. The findings

confirm some of the expected findings in team cohesion dynamics by Kozlowski & Chao (Kozlowski & Chao, 2012). The results reveal that these dynamic team processes occur in a collaborative learning context, which has numerous implications for instructional pedagogy. For instance, teams who are not cohesive throughout their study program are likely to be vulnerable in their performance, leading to the loss of collaborative learning benefits. These teams will be disadvantaged compared to cohesive teams with higher cohesion scores. Therefore, future work is required to identify un cohesive teams and predict the symptoms that cause teams to disagree. With the identified causes, instructors and educators can support vulnerable teams to mitigate the negative effects on the collaborative learning experience.

RQ2: Characterising team cohesive perceptions with performance, engagement and synchrony

The characterisation of cohesive perceptions and evolutions by their learning constructs, such as performance and learning engagement, revealed interesting insights that were both anticipated and unexpected. The expected insights included lower performance scores for teams with different cohesive perceptions. The rationale for this conclusion is that teams who are not task-cohesive will eventually yield lower performance levels than those that are task-cohesive. Similar results are found in collaborative learning and organisational sciences (Grossman et al., 2021; Zamecnik et al., 2022c). However, an unexpected insight revealed that teams who changed between cohesive perceptions from week one to week three had similar performance scores that did not differ longitudinally. In addition, teams that change from their week one perception have comparable performance scores to those that remained in similar perceptions throughout the program, albeit slightly less but not significant. The unexpected discovery may be due to the team's fluctuating cohesion over time based on events that positively or negatively affect their experience. What causes the fluctuations are unknown, and further studies are required to identify these shifts. However, fluctuation of cohesion is a 'normal' experience in

teams and can vary when teams work towards a common goal (Kozlowski, 2015). To accurately capture cyclic fluctuations, novel approaches utilising trace data with known events that can be triggered, such as assessments or tasks that often challenge the team, are required for analysis. On the other hand, the evolution in cohesive perceptions may not impact the team's overall performance as long there is some similarity. Perhaps a program that runs longer than three weeks may reveal the distinguishment between the changing cohesive perceptions and their overall performance. Nevertheless, the insights reveal that teams who do not change cohesive perceptions have significant performance differences in collaborative learning. Therefore, attention is required to delve deeper into their team and learning processes to understand the cause.

Insights related to the team learning engagement were unexpected. There were no significant differences between the evolution groups regarding their collaborative learning, even though some performance scores were significantly different. Given the nature of teamwork, the calculation of team averages from learner trace data may not be enough to characterise cohesion (Treuer et al., 2018). However, exploring team cohesion based on their temporal motif characterisations (i.e., the five motif groups), which was first applied in Chapter 5, shows intriguing insights and offers an alternative approach that goes beyond the summarisation of engagement counts. As such, there are visible interactions between team members that differ based on their group synchrony and motif characteristics, even though their engagement with learning resources was similar.

The findings in this analysis from the characterisation of each evolution group and their five motif groups are intriguing. The dyadic motifs are the only motif group with clear distinctive patterns for teams with similar or different cohesive perceptions. Teams with similar cohesive perceptions have lower dyadic interactions, and teams with different cohesive perceptions have higher dyadic interactions with learning resources. Given that teams with similar cohesive perceptions have higher task cohesion and performance based on the results in this chapter, these findings corroborate the previous studies in Chapter 5. The findings in this chapter give credence to existing theoretical assumptions that using temporal network motifs

through the learners' synchronous interactions with learning resources demonstrates that it is a reliable proxy for cohesion (Forsyth, 2021; Swol & Kane, 2019). Future studies may need to pivot towards trace data exhibiting emergent state patterns and beyond counts. Namely, dynamic interactions that explore team processes using network methodologies to illustrate the reciprocal connections between team members (Mohammed et al., 2021; Santoro et al., 2015). Therefore, applying temporal methodological approaches, such as temporal network motifs, to identify the delicate behavioural patterns that indicate cohesion is one way to measure the complexities of cohesion and further research.

Another fascinating insight from the study is the temporal developments of accumulative network motifs for each evolution group. Evolution groups 1 and 3 share similar developments of temporal motifs, where triadic motifs such as chaotic, ordered, star and switch dominate over the dyadic interactions. These patterns corroborate with the results from Chapters 5, where triadic interactions are discussed that indicate better cohesion and learning outcomes from team members than interactions that are dyadic. It is interesting to observe that teams with similar cohesive perceptions represent similar characteristics to team cluster 1 in Chapter 5. For evolution groups 2 and 4, these teams have an overlay of most temporal motifs throughout their three-week program. Interestingly, they both have prevalent dyadic interactions that are distinctively higher than groups 1 and 3. The findings indicate that teams with different cohesive perceptions have behaviours aligning more with dyadic interactions than triadic ones. Intriguingly, these groups are similar to the findings of team clusters 2 and 3 in Chapter 5. Although, the key difference between the results in Chapter 5 and 6 is that there is a contradiction regarding their performance. Teams related to the findings of Chapter 6 generally have better performance than the teams in Chapter 5. Nevertheless, the work here provides important insights into team behaviours and how they collaborate.

Based on the task cohesion surveys and characterisation of motifs for evolution groups 1 and 3 (i.e., teams with similar cohesive perceptions) and evolutions group 2 and 4 (i.e., teams with different cohesive perceptions), the LA approach is likely

to be generalisable to a certain extent to measure group cohesion in online learning environments.

RQ3: Characterising team cohesive perceptions with feedback

In contemporary literature, feedback delivery is crucial for team learning and cohesion (Gabelica et al., 2012). Feedback may play an identifying role for teams in disagreement, and as a result, it was analysed in this study. Feedback given to teams is strongly connected with their assessment outcomes (Gabelica et al., 2012). Teams prompted with feedback need to reflect on their experiences to continually improve their performance (Gabelica et al., 2014). Another important aspect is the type of feedback that teams receive. Gabelica et al. (2012 have reviewed that certain feedback types are beneficial to enhancing cohesion and performance, such as task and process feedback. Feedback types in this study were analysed based on Hattie and Timperley's (2007) model to characterise the cohesive perceptions. The prominent insights illustrated that teams with similar or changed cohesive perceptions to similar ones have stronger relationships with most feedback types. The insights are intriguing. For instance, feedback on the self is not known to improve learning as it is mainly used for affirmation (i.e. praise or criticism) and has little value in improving performance in learning (Hattie & Timperley, 2007). Currently, there is limited evidence in the literature that shows instructors providing affirmation in their feedback helps to improve the team's cohesion. Another intriguing insight is that teams with different cohesive perceptions received frequent general feedback (i.e., not essential for learning) coupled with task-level feedback. The lack of well-rounded feedback that targets multiple aspects of learning may exacerbate the issue of teams remaining with different cohesive perceptions. In that sense, team performance and cohesion will suffer as there is a lack of feedback focusing on team reflection (regulation) and strategies (processes) that are known to improve performance and cohesion (Gabelica et al., 2012). Arguably, teams that receive well-rounded feedback focusing on the task, process, regulation

and self-level potentially lead to better team outcomes and higher cohesion than feedback that is not well-rounded. The argument corroborates with teams shifting to an agreement where they have received well-rounded feedback.

The literature often mentions the type of feedback the instructor gives in collaborative learning. Although, the research that has comparatively explored the differences between feedback delivered from other stakeholders such as clients, mentors, instructors and peers is unknown. The feedback findings in Section 6.5 indicate that mentors have a stronger relationship with all feedback components provided to teams, especially regulation, than the client. The findings indicate that a client's feedback is shallow compared to mentors, where teams may not receive the support needed for learning development. A possible explanation is that the client's role focuses on how well a team meets the client's requirements. Unlike the mentor, whose role is to support all aspects of team learning, clients may not be aware or concerned about how to provide feedback that improves the health of the team and their learning. Further research that compares the effectiveness of feedback given by different instructors needs to be examined.

6.6 Limitation of the study

The survey questionnaire was restricted to four items and did not utilise the full extent of the remaining questions typically seen in team cohesion studies of a similar context. The decision for the smaller number of questions was based on the educational provider's restricted survey capability, given that they were hosting many other questions to examine different attributes of the teams. Another study limitation is the lack of characterisation of cohesive perceptions and their learning engagement. In LA and EDM, engagement is often used as an indicator of learner performance (Papamitsiou & Economides, 2014). However, the way cohesive perceptions are defined in this study in a collaborative context did not show these connections. Therefore, in future work, analytical techniques considering the dynamic processes of teams that identify temporal reciprocal relationships, rhythms

and fluctuations are recommended to explore for collaborative learning instead of relying on simple statistical summarisation to measure a complex emergent phenomenon. Finally, a three-week full-time course is not a typical study length in most higher education courses. However, notable and relevant observations related to the team's cohesion concur with the existing literature that indicates cohesion manifests relatively quickly (Kozlowski & Chao, 2012). The results give credence to future work in courses longer than three weeks. As such, more evolution points can be observed to understand how team cohesion takes place over a longer duration.

6.7 Implications

There are several practical implications that this exploratory study brings. The study utilises CLA to gain insights into the team's two cohesive perceptions (i.e., similar and different) and how the learning constructs (i.e., performance and engagement) align with those two cohesive perceptions. The results shed some light on the possibility that team members' responses to a task cohesion questionnaire may indicate whether they share similar or differing perceptions of their team's cohesion. Moreover, the findings suggest that cohesive perceptions are likely to be distinguished by their performance scores. Educational providers that facilitate team learning may consider observing these team's states more closely, such as teams that maintain differences in their cohesive perceptions. However, this study was exploratory and limited to a WIL context. Although, the study has the potential to be applied in more TML contexts not limited to WIL. Therefore, further studies could explore if these findings are transferable to other domains. In addition, the study found that teams with different cohesive perceptions are the most vulnerable. They are likely prone to lower team effectiveness based on their lower task cohesion and performance scores while receiving feedback that does not regularly target the team's regulation, self, and process. Future studies are required to explore if findings are generalisable to other learning contexts.

This study also shows insights into providing feedback and cohesion by analysing how different feedback types characterise teams in different states and transitions. Instructors are recommended to provide well-rounded feedback that includes all feedback levels to mitigate team cohesion and performance issues. In that sense, providing teams with feedback targeting their regulation and processes, which is known to help teams in their learning (Gabelica et al., 2012), albeit not regularly provided to learners. Self-guided reflexivity that prompts teams to reflect on their feedback through tools that help with their learning, such as the team LADs, may be an option to enhance team cohesion and effectiveness (Zamecnik et al., 2022a). Future studies that explore the relationship between teams and the feedback they received offers a promising to explore connections with the team's cohesion. As a result, the findings may provide further clarity on how to support team cohesion in similar learning environments.

6.8 Concluding remarks

This chapter characterises team cohesion and their cohesive perceptions in an online environment by their engagement, group synchrony, performance outcomes, and feedback provisions. The main findings arising from this chapter reveals:

- Cohesive perceptions were distinguished based on how similar members rated their task cohesion scores
- The majority of teams begin with different cohesive perceptions in their program and change to ones that are similar by the end
- Teams with different cohesive perceptions have lower task cohesion, performance and feedback
- Teams with similar cohesive perceptions have higher task cohesion, performance and well-rounded provisional feedback
- Cohesive perceptions can be characterised by their task cohesion, performance, group synchrony and feedback, but not learning engagement

Similar findings were discovered in Chapter 5, indicating the generalisability of findings. Regarding performance outcomes, similar cohesive perceptions have higher performance scores than those that differ. Although, performance outcomes are only distinguishable once they have transitioned from week 1 to week 3. Feedback was found to be distinguishable between the cohesive perceptions of teams and their evolutions over time. Teams that receive feedback targeting all levels, including process, task, self and regulation, have similar cohesive perceptions. Teams with different cohesive perceptions received feedback targeted on the task and general level, indicating underlying issues within their work. This study highlights the importance of supporting vulnerable teams in collaborative learning based on their cohesive perceptions and task cohesion.

The overall implications of this study and for the thesis demonstrate that applying analytics-based measures using temporal network motifs from Chapter 5 can characterise cohesive teams. Teams with higher frequencies with triadic motifs indicate stronger cohesion than teams with high dyadic frequencies. Similar results are found in this chapter, where the team's cohesive perceptions remain the same throughout their program and have higher triadic frequencies. The analysis of cohesive perceptions and their corresponding task cohesion scores were based on Carless's (2000) questionnaire. There is a level of credence that teams who exhibit triadic motifs are likely to be team members with similar cohesive perceptions and attributes of higher cohesion. Therefore an essential contribution is made from Chapters 5 and 6 in providing a way for educational stakeholders to measure and analyse the cohesion of teams in technology-mediated collaborative learning contexts.

Chapter 7

Team interactions with learning analytics dashboards

This chapter presents a LAD to understand how teams interact with it and how the dashboard can support team learning in a collaborative learning environment. The research complements the previous studies, which outline a need to support collaborative learning and cohesion teams. This work addresses research aim four, which focuses on how dashboards can support team learning. A paper describing the work contained in this chapter has been published in Computers & Education (Zamecnik et al., 2022a).

7.1 Introduction

The fourth research aim is to develop and evaluate a LAD that aids teams in monitoring and regulating their collaboration based on their perceptions and interactions with the LAD. The outcome of the research aim will address the gaps in understanding how teams interact with a LAD and supports collaborative learning. This Chapter presents the results and discussion of the dashboard for collaborative learning and how to further extend the capability of the dashboard to understand and support team cohesion. The focus of this study is to investigate

how teams interact with the Learning Analytics Dashboard (LAD) in the context of team-based learning. Specifically, the study aims to explore the extent of teams' interactions with the LAD and how they utilise it. In addition, the study seeks to uncover students' perceptions of the usefulness of the LAD during team-based learning and how they perceive the impact of the LAD on their collaborative learning experience. The overall goal of the research questions is to provide insight into the effectiveness and role of the LAD in team-based learning environments, as perceived by the students themselves.

Section 2.4 in Chapter 3 contains extensive literature that motivates the research questions in this Chapter. The study builds on the previous work in Chapters 5 and 6 to some degree by providing an opportunity to incorporate these approaches in future research. This chapter plays a role by helping to address some of the gaps identified in Chapters 4 in this thesis. Namely, how LA tools such as dashboards could facilitate team cohesion while supporting collaboration and team workflow processes in TML environments.

The methodology involves the development of a team LAD that contains log trackers to capture how teams had interacted with it over time to inform on their team's workflow and collaborative learning. Surveys tools have been used to understand how teams perceive the usefulness and ease of use of the dashboard by detailing tables and graphical illustrations to enhance interpretability. Finally, a thematic analysis was conducted based on the video and audio transcripts collected from focus group interview participants.

The chapter is organised as follows: Section 7.1 provides an overview of the state of the LADs and highlights the limitations of existing work in collaborative learning. Section 7.2 provides information on the research questions, while Section 7.3 provides the study design and data analysis. Section 7.4 shows the results of the mixed-method approach. Section 7.5, 7.6 and 7.7 provide this work's interpretations, limitations, and implications, respectively. This chapter is concluded in Section 7.8 with a study summary.

7.2 Research questions

This study focuses on how teams in a K-12 challenge-based learning environment use the learning analytics dashboard to monitor their learning and how the dashboard is helping teams regulate their collaborative learning activities. . As a result, the current study addresses the following three research questions:

- RQ1: To what extent do teams interact with the LAD and how?
- RQ2: What are the perceptions of students on the usefulness of the dashboard when engaged in team-based learning?
- RQ3: What are the perceptions of students on the impact of the dashboard on their collaborative learning experience when engaged in team-based learning?

7.3 Methodology

This section describes the research methodology used to investigate the research questions, including the research design, data collection methods, and data analysis procedures.

7.3.1 Study design

This study took place at an Australian Vocational Education and Training (VET) program where students work towards their Certificate III at a High School. Students engaged on 21st-century Challenge-based learning platform developed by a university provider[1]. The platform is designed to support students' learning in individual and team-based contexts, focusing on open-ended problem-based learning (Gibson, 2018; Ifenthaler et al., 2020). Specifically, it supports self-directed learning, establishing teams, promoting learning strategies and timely feedback.

[1] Challenge platform

To successfully pass the program, teams had to demonstrate the required knowledge and develop the necessary skills to perform tasks in a workplace situation. Each team member is assessed based on collaboration, problem-solving, communication skills, resilience, collegiality, loyalty, and support. The evaluation involves the instructor carefully considering each artefact that is submitted. Team members not meeting the assessment requirements are provided feedback to improve their work and are invited to resubmit their deliverables.

There were 21 students divided into eight teams containing three to four members per team, including a nominated team or group leader. The teams participated in a 20-week blended learning environment working together to improve their collaboration, problem-solving and lifelong learning skills while being coached by the instructor. The assessments have been structured into three major deliverables split into 26 tasks and divided into 91 artefacts that match specific learning outcomes from the units of competency required for the VET Certificate III. For students to complete their VET program and achieve their Certificate III, they must work together by completing artefacts. Students upload artefacts to the platform, which team members improve on before submitting them to the instructor for assessment. Artefacts that the instructor accepts are defined as published. Each team receives feedback for each artefact submitted, supporting their learning activities.

The design of the LAD included multiple iterations of development and testing using an agile methodology by researchers and instructors to ensure that the LAD is fit for purpose. Given that existing LADs were unsuitable for the challenge-based platform, the study included designing a dashboard that caters to the environment for the analysis of the study. The design of the LAD incorporated the five-stage workflow based on the LATUX guideline principles by Martinez-Maldonado et al. (2015b): 1) Problem identification; 2) Low-fidelity prototyping; 3) Higher-fidelity prototyping; 4) Pilot studies and; 5) Validation in-the-wild approach (classroom use). These principles were utilised to create a learning experience for students underpinned by fidelity using learning analytics approaches. As such, the creation of engaging UI/UX designs and visualisations that complement

the learner's pedagogical environment by engaging with researchers, instructors and course developers.

The LAD in this study complements the Challenge learning environment and provides insights and feedback to teams about their learning progress and team interactions. Visualisations, such as network graphs, bar charts, heat maps and tables, have been successfully used in CSCL to inform teams of their collaborative interactions (Liu & Nesbit, 2020). The same visualisations were proposed for the design of the dashboard. Overall, the dashboard consisted of six main visualisations designed to support teams in monitoring their interactions and learning.

- Team Collaborative Network: bipartite graph showing how teams interact with their deliverables.
- Artefact Interaction: bar plot and heat map illustrating team interactions.
- Feedback Comments: infographics of tables related to feedback.
- Artefact Progression: infographics of tables related to artefacts.
- Task Progression: infographics of tables related to tasks.
- Learning Outcomes: infographics of tables related to learning outcomes.

These visuals will help teams monitor work progression, learning outcomes and reduce cognitive load. In addition, the LAD also included a comprehensive filtering capability to sort through dates, tasks and the specific interactions of a team member and team leader. The LAD was introduced later during Week 6, as data needed to be collected from the platform before providing team visualisations. Examples of Team Collaboration Networks, Artefact Interaction, and Learning Outcomes are shown in Figure 7.1, 7.2 and 7.3 below.

Student interactions with the LAD's visuals are captured using an inbuilt log tracker to understand their use. Identifying and evaluating student behaviours is crucial when designing effective LADs to cater for their needs (Verbert et al., 2020).

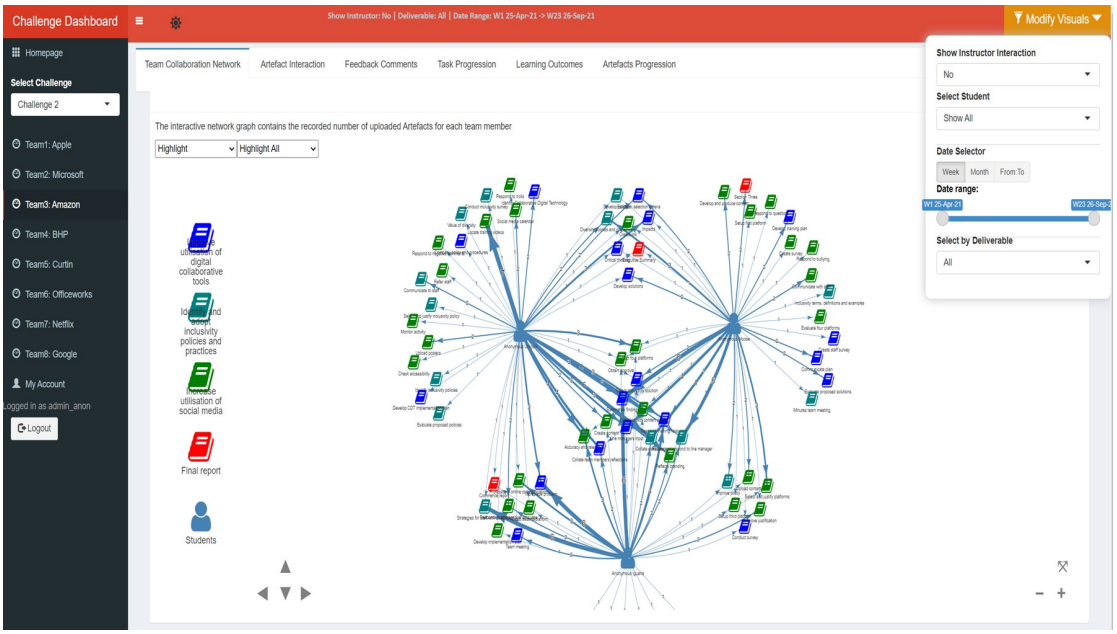


FIGURE 7.1: Example of the LAD Team Collaboration Network (Zamecnik et al., 2022a)

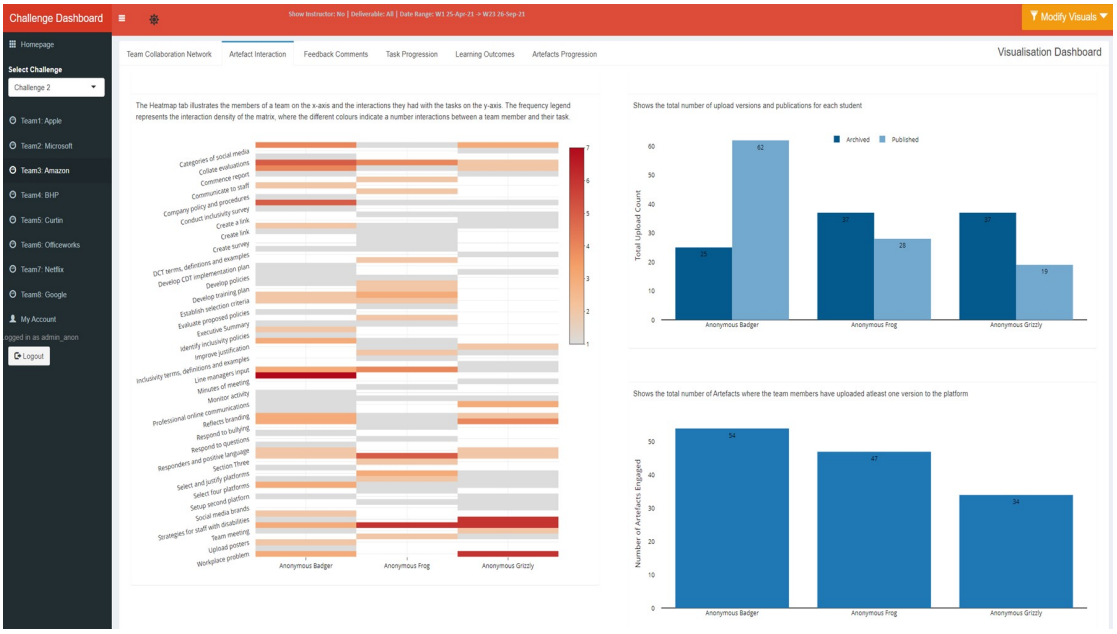


FIGURE 7.2: Example of the LAD Artefact Interaction (Zamecnik et al., 2022a)

For instance, teams may have engagement behaviours associated with particular learning strategies when interacting with the dashboard defined by the roles of the team. That being said, the research that identifies characteristics of team learning behaviours or strategies when using LADs is limited. Within the current literature, there is limited research about the roles of teams, their engagement with LADs over time, and what inferences can be made about their learning and performance.

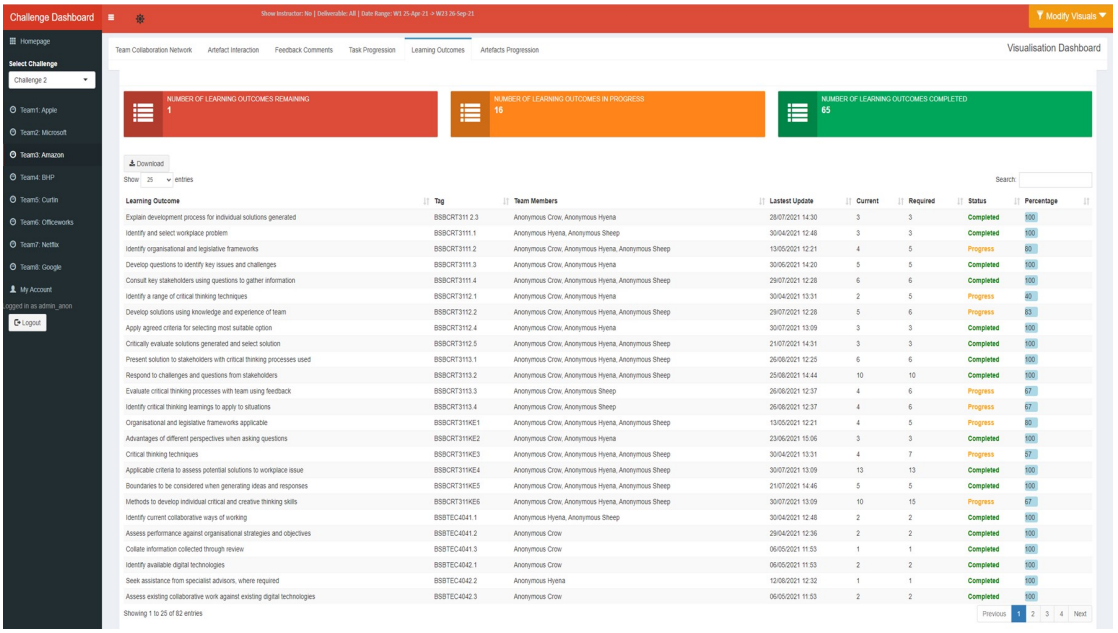


FIGURE 7.3: Example of the LAD Learning Outcomes (Zamecnik et al., 2022a)

LADs capable of tracking students, similar to how modern learning management platforms capture students' logs, is one way to provide valuable insights towards improving the LAD and establishing a richer understanding of the connections with their collaborative learning behaviours.

7.3.2 Data analysis

This study collected data on how team members (n = 21) interacted with the LAD and the Challenge learning platform. Further, the team's summative assessments were collected, and a qualitative survey (n = 19) and a focus group (n = 6) were undertaken to gather further insight into using the dashboard. The dashboard interaction (i.e. trace data) data was collected. The raw data included the team member ids, the timestamp of interaction, and the specific event they interacted with in the LAD, such as viewing a team's visualisation and filtering specific observations of that visual (i.e. highlighting team member interactions with an artefact). In this analysis, the raw data from the event log is translated into an interpretable one. Learning analytics approaches were used to analyse team engagement by calculating their average time spent, the number of sessions and

interactions with the six visual plots of the LAD. The trace data contained some clicks from team members either done with an error or irrelevant to their learning when navigating the LAD. Laborious efforts were made to mitigate data errors to ensure the reliability of trace data in this analysis. This included removing data duplication, incomplete interactions, and data unrelated to a student's learning.

Research in learning analytics demonstrates the importance of using trace data to make inferences about self-regulated learning, academic performance, and metacognition (Hadwin et al., 2007; Jivet et al., 2021; Winne, 2020), to name a few. Hadwin et al. (2007) found that trace data is important for defining strategies and sequences in self-regulated learning. Trace data contains fine-grained study actions more so than self-reports, as trace data shows evidence of learning. Studies by Jivet et al. (2021) have demonstrated the usefulness of using trace data by capturing learning indicators of students and what they prefer to see in the LAD, such as the completion of their learning activities. In this study, the LAD captures the trace data for each team and uses learning analytics approaches to understand the extent (i.e. the number of interactions) to which teams cognitively engage with the LAD and how those interactions corroborate with their learning.

A qualitative survey was conducted based on the technology acceptance model (TAM) to determine the perceived usefulness (PU) and perceived ease-of-use (PEOU) (Davis, 1989) of the LAD. They were adjusted from the original questions (1989) to reflect the collaborative learning context. Questions related to the TAM survey can be found in Appendix B.1. Finally, a focus group interview was conducted where transcript data was collected from students regarding their perspectives of the LAD in their collaborative learning experience. As such, inductive thematic analysis was conducted to identify patterns and themes in the focus interview data. The six phases of thematic analysis were followed according to Braun and Clarke (2006), which includes: 1) familiarisation with the data; 2) generating initial codes; 3) searching for themes; 4) reviewing themes; 5) defining and naming themes and; 6) producing the report. Inter-rater reliability was not recorded for the thematic analysis when coding the transcript data. The nature of the transcript data did not present any complexities or nefarious issues which

could cloud judgement and require the need for an inter-rater for clarification. The questions related to the thematic analysis can be found in Appendix B.2.

7.4 Results

7.4.1 Dashboard interactions

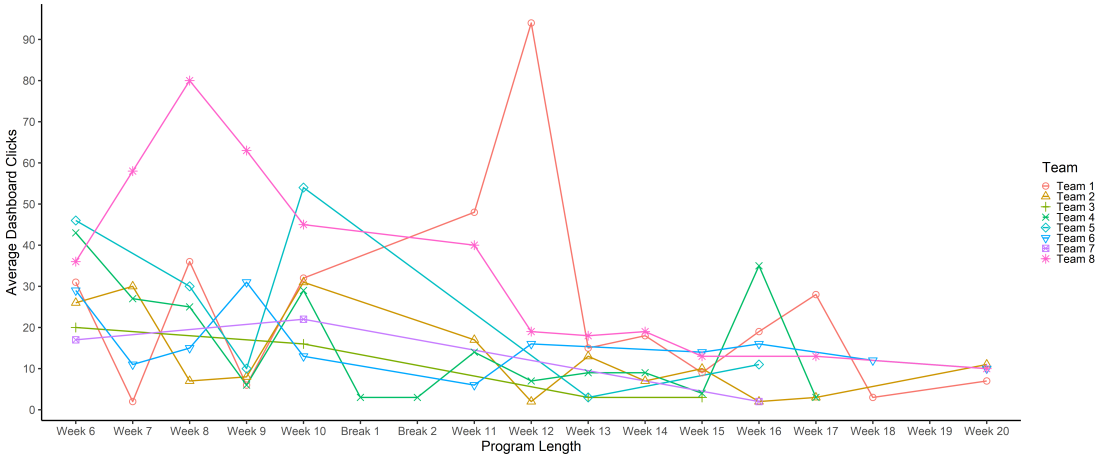


FIGURE 7.4: Average number of clicks spanning Week 6 to Week 20 for each team (Zamecnik et al., 2022a)

Fig 7.4 shows each team's average number of clicks weekly from Week 6 to Week 20. The results show that teams (i.e. Team 1, Team 2, Team 4, Team 6 and Team 8) are mostly consistent with using the LAD every week instead of other teams with more inconsistent engagement behaviours (i.e. Team 3, Team 5 and Team 7). Consistent teams (i.e., Team 1, 2, 4 and 6) prefer to regulate more often than inconsistent teams (Team 3, 5 and 7). Specifically, Team 8 had the highest number of clicks before week 11. As a result, the team members had been regulating extensively in the program's first half before tapering down. Team 1 shows that they had the most clicks between weeks 11 and 13, indicating an event where high regulation occurred. Moreover, the results show that during Week 6 (introduction week) all teams engaged at a moderate level, with at least 17 interactions per team. Teams have a two-week break (i.e. Break 1 and Break 2) after week 10 and are not required to study unless they wish to. Moreover, from

Week 12 to Week 16, the average number of dashboard engagements decreased for most teams. It is likely that some teams finished the program earlier, while others learned how to navigate the system more efficiently with fewer clicks.

TABLE 7.1: Average engagement interactions for each team with challenge platform between Weeks 1 – 5 (before the introduction of the dashboard) and Week 6 – 20 (after the introduction of the dashboard)

Team	Week 1 - 5		Week 6 - 20		
	Uploads	Publications	Uploads	Publications	Dashboard Interactions
Team 1	1	3	6	3	25
Team 2	3	3	5	4	13
Team 3	2	3	6	3	11
Team 4	4	3	6	2	16
Team 5	4	3	6	4	26
Team 6	3	2	4	2	15
Team 7	4	3	5	3	14
Team 8	6	5	6	2	35

Note. The dashboard has been introduced in Week 6.

Table 7.1 shows each team's average number of uploads and publications of artefacts from Week 1 to 6 and Week 6 to 20. The results show that before introducing the LAD, there have been an average of 3 artifact uploads while after the introduction there have been on average of 6 uploads from Week 6 to 20. However, the results had no changes in published artifacts, with the average publications remaining the same between Weeks 1 to 6 and Weeks 6 to 20. The table also shows the average engagement of the LAD per team in clicks with the dashboard. For Weeks 1 to 6, there was no engagement with the LAD, as it was not yet introduced until week 6. The Wilcox test showed no statistically significant differences in the number of publications between Week 1 – 5 and Week 6 – 20 between the teams.

Table 7.2 shows how students in two different roles (i.e., team member and team leader) engage with the six main visualisations of the LAD (i.e. Team Collaborative Network, Artefact Interaction, Feedback Comments, Artefact Progression, Task Progression and Learning Outcomes) and how they differ in interactions. The findings indicate a trend where the team leader is generally less engaged (i.e. 22 clicks on average) than with Team members (i.e. 44 clicks on average) with the Team Collaborative Network. However, regarding what team leaders interact with

TABLE 7.2: Total engagement (Te) and the distribution of clicks (%) with the dashboards visualisations by each team leader and team members per team)

Team & Role	Collab Network		Artefact Interaction		Feedback Comments		Artefact Progress		Task Progress		Learning Outcomes	
	Te	%	Te	%	Te	%	Te	%	Te	%	Te	%
Team 1 - TM	59	49	14	12	12	10	15	13	12	10	8	7
Team 1 - TL	54	50	5	5	7	6	25	23	8	7	10	9
Team 2 - TM	26	47	5	9	4	6	16	27	3	5	3	5
Team 2 - TL	47	72	1	2	4	6	10	15	2	3	1	2
Team 3 - TM	8	44	0	0	1	6	7	39	1	6	1	6
Team 3 - TL	22	92	0	0	0	0	2	8	0	0	0	0
Team 4 - TM	38	46	6	7	6	8	24	28	6	7	4	5
Team 4 - TL	20	41	1	2	5	10	18	37	2	4	3	6
Team 5 - TM	28	43	2	2	6	10	24	37	2	4	4	5
Team 5 - TL	8	40	0	0	1	5	9	45	1	5	1	5
Team 6 - TM	39	50	13	17	6	7	14	18	4	5	2	3
Team 6 - TL	15	50	0	0	2	7	12	40	0	0	1	3
Team 7 - TM	21	51	0	0	3	7	13	32	2	5	2	5
Team 7 - TL	0	0	0	0	0	0	0	0	0	0	0	0
Team 8 - TM	131	59	18	8	12	5	38	17	11	5	12	5
Team 8 - TL	11	85	0	0	0	0	2	15	0	0	0	0
Team Avg - TM	44	49	7	7	6	7	19	26	5	6	5	5
Team Avg - TL	22	56	1	3	2	5	10	26	2	5	2	5

the most regarding the LAD visualisations, The Team Collaboration Network is the most popular, with 61%. In contrast, the Team members spend 48% of their interactions with that feature. Overall, the findings indicate a trend where team members interact more with the LAD visualisations than team leaders for each team.

TABLE 7.3: Wilcox test of the total clicks with the dashboards visuals of the team leader and team member groups

Variable	Static	p-value	Size Effect	Magnitude
Team Collaborative Network	17.50	0.14	0.38	Moderate
Artefact Interation	12.50	0.04*	0.54	Large
Feedback Comments	13.00	0.05*	0.50	Large
Artefact Progression	15.00	0.08	0.45	Moderate
Task Progression	10.50	0.03*	0.57	Large
Learning Outcomes	12.00	0.04*	0.53	Large

Note. * indicates statistical significance at 0.05 level.

Table 7.3 shows the reported p-values using the Wilcox test for non-parametric values and the reported size effect between teams' roles and their interactions

with the LAD visualisations. The results indicate statistically significant differences $p < 0.05$ in Artefact Interaction (i.e., the statistic of $U = 12.50$), Feedback Comments (i.e., the statistic of $U = 13.00$), Task Progression (i.e., the statistic of $U = 10.50$) and Learning Outcomes (i.e., the statistic of $U = 12.00$), all with large size effects (i.e., 0.54, 0.50, 0.57 and 0.53), respectively. There were no significant differences between team roles between the Team Collaboration Network or Artefact Progression.

TABLE 7.4: Counts of the session average, duration average and engagement average with the dashboard for each team role

Team	Role	Session Average	Duration Average	Engagement Average
Team 1	TM	8.85	0.56	13
Team 1	TL	7.79	0.59	12
Team 2	TM	6.00	0.35	11
Team 2	TL	7.22	0.15	8
Team 3	TM	6.00	1.83	2
Team 3	TL	6.00	1.22	4
Team 4	TM	7.30	0.76	14
Team 4	TL	7.00	0.85	4
Team 5	TM	11.17	0.57	6
Team 5	TL	10.00	0.93	2
Team 6	TM	11.00	0.26	11
Team 6	TL	6.00	0.79	4
Team 7	TM	6.83	0.14	3
Team 7	TL	0.00	0.00	0
Team 8	TM	10.28	0.75	12
Team 8	TL	4.33	1.04	2
Team Avg	TM	8.40	0.65	9.00
Team Avg	TL	6.00	0.70	5.00

Table 7.4 shows the Session Average, Duration Average and Total Presence with the LAD between teams and their roles. The results indicate that, on average, Team members have 8.43 (σ 2.18) and team leaders have 6.00 (σ 2.93) sessions, a difference of two sessions. The Duration Average for each session shows minuscule differences between the team roles. The Engagement Average for Team members indicates that team leaders engaged with the dashboard for an average of at least 5 weeks out of the 14-week period from Week 6 to Week 20, while team members engaged with the dashboard an average of at least 9 times per week.

TABLE 7.5: Wilcox test of the session average, duration average and engagement average variables between team leaders and team members

Variable	Static	p-value	Effect Size	Magnitude
Session Average	17.00	0.12	0.39	Moderate
Duration Average	41.00	0.37	0.24	Small
Engagement Average	15.50	0.09	0.44	Moderate

Table 7.5 shows the reported p-values using the Wilcox test for non-parametric values and the reported size effect using the 'rstatix' R package between the roles of teams with the LAD. The results indicate no statistically significant differences between team roles with regard to session average, duration average and engagement average.

TABLE 7.6: Final scores for the Challenge platform and total and average interactions with the dashboard interactions per team

Team	Final Scores	Total Dashboard Interactions	Average Dashboard Interactions
Team 1	82	348	25
Team 2	74	167	12
Team 3	71	42	11
Team 4	72	217	16
Team 5	72	154	26
Team 6	78	173	15
Team 7	56	41	14
Team 8	65	414	35

Table 7.6 shows the final scores received by each team from a maximum score of 100 and their associated dashboard interactions by total and average through their program. The Spearman's rank correlation was undertaken to correlate team scores with the total and the average number of interactions with the LAD. The results indicate no association between the teams' final score and their interaction with the dashboard.

7.4.2 Impact of the dashboard for collaborative learning

A Technology Acceptance Model (TAM) (Davis, 1989) survey was conducted and modified to closely represent the effectiveness of the dashboard in collaborative learning settings to examine the perceived usefulness (PU) and ease of use (PEOU)

of the LAD for collaborative learning. The results in Fig 7.5 show 12 questions, where Q1-Q8 represents PU and Q9-Q12 represents PEOU factors. The factors were then analysed using Cronbach's alpha (1951), and the measures found to demonstrate strong internal consistency and exceeding reliability estimates ($\alpha = 0.70$) (Nunnally, 1978), as shown in Table 7.7.

TABLE 7.7: Cronbach alpha reliability coefficient

Factor	Items	Alpha
Perceived usefulness (PU)	8	0.82
Perceived ease-of-use (PEOU)	4	0.87

The descriptive statistics of the two perceived factors in Table 7.8 show that the means are above the midpoint of 3.63 and that the standard deviation ranges from 0.61 to 1.08, indicating a small spread from the mean. The results from the TAM survey show that teams rated perceived usefulness and ease of use highly, with an average rating of 4 out of a maximum of 5.

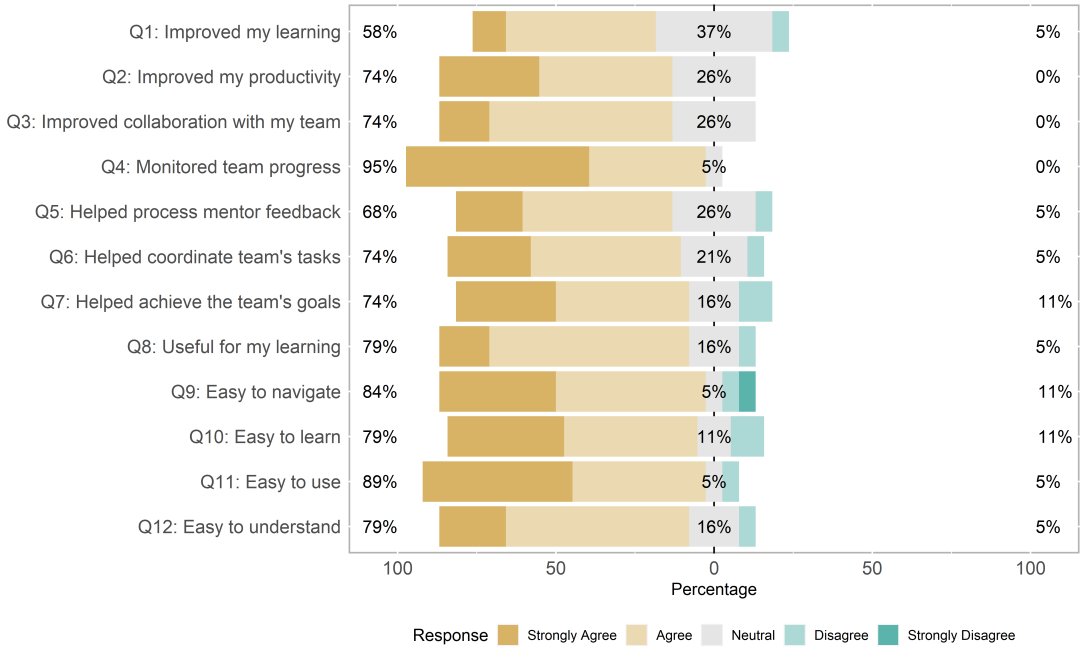


FIGURE 7.5: Survey for perceived usefulness (PU) and ease-of-use (PEOU) of the LAD (Zamecnik et al., 2022a)

In Fig 7.5, the response rates from the students for the PU factor are on the agreement spectrum related to the perceived usefulness of the LAD. Specifically, teams found that the LAD helped monitor team progress, improve their productivity,

TABLE 7.8: Summary of means and standard deviation (n = 19) for the Technology Acceptance Model (TAM) survey

Factor	Question	Mean	Std dev
Perceived usefulness (PU)	Q1.	3.63	0.76
	Q2	4.05	0.78
	Q3	3.89	0.66
	Q4	4.52	0.61
	Q5	3.84	0.83
	Q6	3.94	0.85
	Q7	3.94	0.97
	Q8	3.89	0.73
Perceived ease-of-use (PEOU)	Q9.	4.05	1.08
	Q10	4.05	0.97
	Q11	4.31	0.82
	Q12	3.94	0.78

achieve the team's goals and coordinate the team's tasks. The results from the PEOU factor also indicate that the respondents agree that the LAD is easy to navigate, learn, use and understand.

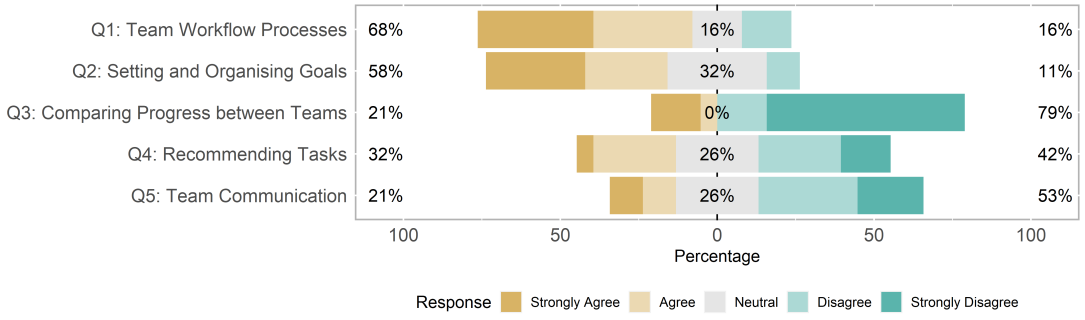


FIGURE 7.6: Additional proposed functionality of the LAD ranked by importance (Zamecnik et al., 2022a)

The results in Fig 7.6 show the response rates of how students ranked the five desired improvements for the LAD. As such, students agree to a large extent with adding capabilities for team workflow processes and setting goals instead of comparing progress between teams, recommending tasks, and team communication.

7.4.3 The perceptions of the dashboard for collaborative learning

A focus group involving six students was conducted by asking them questions about how the LAD impacted their team's strategies, monitoring, and organisation in the collaborative learning environment to examine students' perceptions. They expressed a variety of opinions and feedback on the LAD. As a result, three themes emerged: 1) Regulation and workflow; 2) Impression and evaluation and; 3) Perspectives. These themes were generated by turning several codes identified from the transcript into consolidated themes. Codes that did not appear regularly in the transcript were discarded. Overall, based on the theme of the questions given to the focus groups, the six students often mention the topic of teamwork, the LAD helping with their collaboration and sharing their thoughts and opinions about the LAD in several different learning scenarios. Further descriptions of each theme and examples are discussed in the next subsections.

Regulation and workflow

Team members found that the LAD has benefits for their collaborative learning. The LAD allowed teams to strategise their collective learning by understanding the capabilities and needs of their team members, indicating behaviours that promote socially shared regulated learning (Hadwin et al., 2011): *"With the collaboration network, it allowed us to see who was doing what work and how much. So, I all got an equal amount of work or who was working on what so I could help each other out."* Some team members choose to learn at their own pace instead of rushing to clear all the artefacts that closely relate with self-regulated learning characteristics (Hadwin et al., 2011): *"We like, highlighted the different characteristics of a lot of the team members, kind of able to like set a strategy around them, kind of give people work that best suits them, kind of adjust things."*

Our results also show that students are encouraged by the visual outputs from the LAD by realising their progress, identifying social loafing issues with team

members and helping to organise strategies to carry out their tasks: *"Tells me if I am working slow at a slower pace and if I need to like just catch up a bit. It's easy to like look at it and go, OK, so we need this person to complete something in this artefact so they can also get ticked off."* Students also reported that the LAD significantly helped monitor the progression of team members and their work: *"It's like exciting to see like where you've progressed from, like the week before."* Moreover, students found it motivating to use the LAD and embrace the data showing their progression: 1) *"Pretty much every time the data was updated, I went on to the dashboard and I'll discuss with my team, just pointing out how things are."*; 2) *"Just knowing to like what I have to do to spread out like all the other artefacts that I have to do so that I can focus on."*; 3) *"You can see where things are progressing."*;4) *"I really like the bit where you can see all the artefacts done in your team and who is doing what."*

Impression and evaluation

The results from the thematic analysis indicated many observations related to feedback about the visualisations, global views (i.e. seeing information that is not yet made available) and impressions of the LAD in general. As such, students were identified from the focus group are after personalisation from the LAD that includes customisation of text, colour, and additional visualisations to explore and targeted feedback on how to improve their correct artefact: *"It could probably have a greater sense of sort of personalisation. So, to be able to change the look of things, you know, make the text more bold or just accessible for different ways of perceiving sort of information that can be there."* Furthermore, it was reported that students had some initial difficulties in the first week understanding how the dashboard works and how that information is supposed to be interpreted. This finding also corroborates with the results depicted in Fig 7.3, where students spent more sessions during Week 6 (i.e. the first week of the introduction of the LAD), as opposed to the other weeks where the sessions became more normalised: *"I did find it a bit difficult to understand at first. It took a bit to wrap my head around it, but eventually you do get used to it and it does become quite helpful."* However,

students quickly learned how to operate the LAD and found it helpful for their collaborative learning: 1) *"It was a little bit difficult at first, having to constantly like check on it and everything, but then you kind of get used to it and it's like a lot easier to do your work, so it's really handy."*; 2) *"It allows us to see, like, information in my group that we haven't like been able to see before".*

Some students found visual plots in the LAD redundant, such as the feedback comments table, where they already had access to that information elsewhere. The results suggest that a system already in place that performs the same operation or better is redundant in the LAD: *"I prefer to use the X system because that's just where I go to see my feedback initially anyways. So I don't see the point of going onto the tab and seeing it again"* There were also features that students were receptive to, which helped them engage with the LAD and enhance their collaborative learning experiences. Those include interactivity, progression and colour schemes, as shown by the following comments: 1) *"Honestly, the person that I am, my favourite part is definitely the collaboration network just being, oh, yeah, drag people around, that's pretty fun."*; 2) *"It's nice to have different colours, and that's definitely a positive."* Moreover, students reported new experiences that helped them to organise themselves and their teams that they were not able to view before: 1) *"There was a lot of data that was sort of like, wow, you know, this really shows us what we've got to change or what we've got to improve."*; 2) *"Being able to see all the work that's been done, it really helps just organise things better and get things done, especially with the task progression, the number of tasks remaining and the task and progress, it lays it instantly in front of you and it really helps."*

Team wellbeing and emotion

Psychological safety was another theme that has arisen from the findings. One student reported: *"To be honest, we didn't discuss the dashboard too much with my team, but in any conversation, we did have about the dashboard, I was able to express my thoughts."*. As such, psychological safety allows a team member to feel

safe and allows for moderate risk-taking, creativity and being vocal with one's self-thoughts and opinions (Edmondson, 1999). Another student reported: *"Every time the data was updated, we went on the dashboard and we discussed it in our team, just pointing out how things are going and I never really felt any embarrassment when talking to my team, like if I was falling behind, oh I'm falling behind, could you guys give me some assistance on the next deliverables and what not?"* However, psychological safety in LAD research is underexplored and little is known about this phenomenon.

Based on the thematic analysis undertaken, the identified themes were related to psychological safety. As such, the students discovered had expressed their initial feelings when using the LAD, such as the worries they had and their thoughts on any potential punishment or embarrassments while using the dashboard in their team (i.e. underperforming in a team): *"At the start, I think I was a bit worried, but after a week I was pretty set. It was more of a lack of understanding, but after adapting to it, it was easy."* In the focus group interview, students reported no issues found from the visualisations that showed collaborative issues in the dashboard that negatively impacted the psychological safety of students. Each student in the focus group had different experiences of dealing with any potential psychological safety issues that arose with their team member, demonstrating high levels of collegiality and professionalism: 1) *"Um, I gotta be honest, not really, I think that is probably more of a reflection of me as a person and a team leader, like, I'm not very like, crack the whip, like, get going, I'm more of like an individual who will be like, just do it at your pace, as long as your doing it well, quality rather than doing it fast and just trying to get everything done."*; 2) *"People who were not performing well up to like the standard that we set at the beginning, I kind of made sure that I that I toned back the level of embarrassment."*; 3) *"I think that no one was subject to any embarrassment, I think just in a team setting alone it is important not to feel that way, especially looking at the collaborative stuff, it can be a little be hard when your switching and seeing all this data that compares you against everyone else, but at the end of the day, um, I'm pretty sure we are all*

just a team and you have to be able to use those to your advantage and not let that affect you"

7.5 Discussion

RQ1: Team role behaviours and engagement with LAD

The study applies a novel approach to capture team trace logs from a LAD, revealing insights into how teams use the tool in their learning contexts. Most teams consistently engage with the LAD throughout their study program. Upon initially introducing the LAD in Week 6, engagement with the LAD was higher than in the later stages of their study, indicating sense-making processes, as teams familiarised themselves with the capabilities and usefulness of the LAD to guide their actions (Klein et al., 2007). The findings of higher engagement in the initial stages can be interpreted as an "exploratory phase" for team members as they learn how to use the system. Teams may navigate and click through all the tabs to familiarise how the LAD produces visual results and reiterate that process until the teams grasp the system. After familiarisation, engagement had tapered down throughout the weeks. In sense-making, the potential of teams learning to navigate the LAD and obtain required information can explain the lower number of interactions. Teams had learned to operate the LAD by taking fewer steps to access the information they needed to inform their teams' progress (Martinez-Maldonado et al., 2015b). Moreover, the number of document uploads in the challenge platform had increased two-fold in cases when the LAD was introduced to teams. An explanation for this phenomenon might be attributed to increased visibility of team member efforts and interpretable visualisations of team progress, allowing for easier evaluation of a peer member's contribution. In that sense, the dashboard can encourage teams to think about their accountability due to peer evaluation, reducing social loafing behaviours and increasing effort (Aggarwal & O'Brien, 2008).

The findings also uncovered various team roles expressed through their engagement with the LAD. It was expected to find team leaders with higher engagement across the board compared to team members, given that team leaders naturally have a strong role in task leadership by monitoring progress, coordinating tasks and maintaining communication with the team (Burke et al., 2006). However, team members have a higher overall engagement with most visualisations in the LAD than team leaders. An explanation may be attributed to how team members conducted regulatory processes, such as actively engaging with the dashboard to monitor their team's performances, the completion of tasks assigned to them, tasks assigned to others and to help coordinate the next activity (Järvelä & Hadwin, 2013). Given that the LAD illustrates evidence of team learning, it may pressure members to be accountable (Laal & Ghodsi, 2012). Team members may need to contribute to limit themselves from appearing as free riders. The lower engagement from leaders may be attributed to their focus on delegating tasks and monitoring the team's overall progress. The implications of team leaders engaging less with the LAD, as opposed to other roles, needs to be carefully considered when designing dashboards in team-based environments to ensure that the visual information complements their role.

The reported average of one minute per session in the findings may indicate that students did not find the LAD engaging. Although dashboards are designed to provide easily digestible information for the end-user to make accurate and quick decisions and not distract them from their work (Few, 2006). Therefore, teams that spend less time on the dashboard may suggest that they can process information quickly. Upon further examination regarding the engagement of team roles in the LAD with the visual features, the team network graph had the most interactions. The findings reported in the survey and focus group suggest that the networks helped the team monitor, strategise, and understand the contribution and progress of their team. Graphs, when structured well, can inform teams on 'who collaborates with who' and 'who does what' (Chounta et al., 2014; Kerrigan et al., 2019). The finding is important, as networks illustrating interactions between team members and their tasks in collaborative learning literature is sparse.

Network analysis has been a cornerstone of LA (Du et al., 2021) and should be considered in future collaborative learning environments to support teams. The implications for designing LADs with network graphs in team learning are important, as the results in this study show the tendency to promote team regulatory processes.

Intriguingly, Team 8 had the most interactions with the dashboard in the program's first half and received one of the lowest assessment scores in this cohort. Although, the team leader in Team 8 interacted disproportionately less than their team members. The finding suggests a lack of effective metacognition from the leader concerning planning tasks, actions, and strategy use (Duffy et al., 2015). Another explanation may be ineffective strategies used to regulate their learning and a lack of understanding of the requirements. Team 1 had the highest assessment scores and the second-highest engagement with the LAD. Although the team was consistent throughout the program, the findings show a large spike in interactions with the LAD compared to others shortly after their term break. Motivation and eagerness may have played a role in reminding them of their current progress. Motivated students show elevated levels of self-regulation and achieve higher academic performance than unmotivated students (Zimmerman & Schunk, 2008). Finally, the findings show limited relationships between team dashboard interaction with task engagement and performance. Future research on those relationships should include more teams in similar settings to establish construct validity.

RQ2: Impacts of LAD on the collaborative learning experience

The second question examined the LAD's perceived usefulness and ease of use in collaborative learning. The findings demonstrate that they become helpful and engaging when design principles occur for LA visualisations (Martinez-Maldonado et al., 2015b). Moreover, participant responses indicate that the LAD is practical for monitoring teamwork, which is also reflected in the focus group participants. The

result is unsurprising as the tool was specifically designed to help teams monitor collaboration and ease the cognitive load. LADs, when designed to function together with the associated learning platform it draws data from, can be a powerful tool for teams to help with their learning (Liu & Nesbit, 2020).

The responses provided by students to rank the features for a future LAD came as a surprise, as students were not receptive to team communication illustrations. Instead, they favoured other capabilities that enhanced their workflow and progression. The importance of this finding is notable, as most group awareness tools and dashboards in existing literature commonly use communication visualisations within groups to measure networking ties or participation levels (Han et al., 2021; Liu & Nesbit, 2020). Moreover, the students ranked the comparison of progress with others low. As such, teams may feel uncomfortable with gamified or competitive-based learning. However, there may be potential issues with psychological safety. Further research is required to understand the psychological safety phenomenon in a follow-up study regarding what these insights mean. Regarding what students ranked the highest, more capabilities with monitoring workflow processes and the ability to set and organise goals are of the highest priority. This finding suggests that students prefer LAD capabilities that enhance their SSRL (Hadwin et al., 2011), which helps teams direct their learning.

RQ3: Student perspectives with the LAD

Finally, the third question examined participants' perspectives in a focus group that examined the LAD and its impacts on collaborative learning. The findings revealed three themes that were observed in the focus group.

The first emergent theme, workflow and regulation, revealed that the LAD helped with their team's monitoring, strategy, and organisation. Surprisingly, students found graph-based visualisations highly engaging, as evident by our quantitative and qualitative study results. While graphs illustrating the collaboration of task

interactions within teams are limited in visualisation tools in collaborative learning literature, social network graphs are popular and have been extensively used to illustrate the communication between group members to foster social interaction (Becheru et al., 2018). Increasingly, collaborative illustrations using networks are becoming popular in team learning contexts to understand problem-solving processes (Kerrigan et al., 2019, 2021). However, research providing such feedback for teams in dashboards and other visualisation tools is limited. Consequently, researchers designing LADs for the collaborative learning context must consider such visualisations as they may greatly aid engagement and benefit their learning.

The second emergent theme identified, impression and evaluation, revealed several insights on improvements for the LAD. They should not reinvent the wheel and replicate functionality existing in other systems. In that sense, LADs benefit the most if they include a unique capability for students not available elsewhere. In existing literature related to LADs, this corroborates with the findings of Roberts et al. (2017), suggesting that learning dashboards need customising capabilities to enhance the student's engagement.

Finally, the last emergent theme, team well-being and emotion, provided unexpected novel insights that have not been explored before in LADs regarding the impacts of the psychological safety of teams. With psychological safety is currently underexplored in LAD research (Williamson & Kizilcec, 2022). The findings revealed that the LAD had minimal impact on psychological safety issues. Students reported being open about their progress and not embarrassed when discussing any issues with their team. However, not all participants were included in the focus group, as there may be unreported psychological safety issues. Participants with low contribution levels might have felt uncomfortable, given that the visualisation highlighted their rework and lack of progress. For future research endeavours, the development of LADs in collaborative learning contexts is strongly encouraged to consider the psychological safety of teams before presenting them with data illustrations of their progress. It may cause conflict and impact the collaborative learning experience if the concerns of students are not met.

7.6 Limitation of the study

As in the case of any research study, the study presented in this chapter is not without its limits. The cohort of teams and their size are very small in this study. As a result, the generalisability of the findings is challenging for learning contexts beyond K-12. Furthermore, most teams had different engagement patterns concerning their roles. For instance, some team leaders engaged significantly more with the LAD than other team leaders. It could be that some students may have different strategies when examining their teamwork in the LAD. Third, a further limitation of the analysis is to fully grasp the interactive impacts of the LAD and how that translates to completing tasks and learning outcomes. Challenges arise when drawing direct behaviours of dashboard interaction and relationships with the timeliness of completing tasks. For instance, one can question whether tasks occur immediately or are delayed for weeks. Finally, the study's exploratory nature is recognised as limited when using a LAD for collaborative learning contexts. As such, collaborative learning and the structure of a learning environment are complex and in no way suggest that the LAD is a 'one-size-fits-all' approach.

7.7 Implications

In terms of implications, capturing the team's learning processes within the LAD and establishing deeper connections with their collaborative learning outcomes will further help ground research on team learning. Work could include implementing SSRL capabilities in the LAD that capture how teams direct, control, and negotiate their collaborative learning. It will allow educators to observe learning processes in the LAD arising from the motivational, behavioural and cognitive states and pedagogically support teams by positively nurturing those processes. Thus, helping to increase collaborative learning outcomes in teams. The findings from the assessment of the LAD for team interactions have broader implications for the development of LADs in other contexts. Specifically, teams in the study found that LADs with interactive visualisations were highly engaging and were

able to accurately simulate their workflow progress. This suggests that incorporating interactive visualisations into LAD designs could lead to higher levels of team engagement and better representation of team progress. Therefore, these findings could inform the development of LADs in other team or group settings to improve engagement and workflow visualisation.

7.8 Concluding remarks

In this chapter, the gap in developing a LAD is addressed to aid the collaborative learning experiences and explore how teams utilise and interact with the visualisation tool using inbuilt log trackers. The main findings from this chapter reveal:

- LAD in K-12 collaborative learning promotes engagement and collaboration.
- Team interactions with a learning analytics dashboard can support instructors in assessing and improving collaborative learning behaviours.
- Visualisations illustrating workflow processes of teams foster more engagement with the dashboard compared to typical bar plot visualisations.
- Team members may be more interested in using the LAD to track their own progress and performance, while leaders may be more concerned with using the LAD to identify ways to support and develop the skills and capabilities of their team members.
- K-12 teams perceive the learning analytics dashboard (LAD) as useful in supporting team regulation in collaborative settings.
- Identified a significant theme of psychological safety that is often not considered in related literature.

The literature concerning visualisation tools in collaborative learning contexts has mainly been explored (Liu & Nesbit, 2020). There is a limited number of visualisation tools currently available for collaborative learning environments that are

grounded in established theory and instructional design principles. These tools should be designed to capture student interactions and align them with their course engagement. Future research could investigate the development and evaluation of more comprehensive visualisation tools, which may enhance instructors' ability to monitor and support student engagement and collaboration in online learning environments. Moreover, applying mixed methods to connect with their collaboration experience using LADs is scarce. These gaps lead to the goals for addressing research aim four, supporting team cohesion with LADs.

Chapter 8

Conclusion

The thesis presents several important contributions to learning analytics and collaborative learning. Specifically, it synthesises existing literature on the topic, develops a new analytics-based measure for assessing team cohesion, characterises team perceptions through data analysis, and implements a LAD to support team cohesion in TML environments. The work described in this thesis provides valuable insights for researchers in this area and motivates further exploration of strategies for enhancing team cohesion in TML.

8.1 Research aim one: The cohesion of small groups in technology-mediated learning

Research aim one was addressed in Chapter 4, where two decades of literature from 1995 to 2022 were synthesised based on how researchers measured and analysed group cohesion in TML environments. The study addresses the need to consolidate research on group cohesion to identify gaps and move research in this space forward. A synthesis of the most commonly utilised conceptualisations of group cohesion was performed. The methodological approaches used to measure and analyse group cohesion, and the factors that impact and facilitate group cohesion in TML environments were examined. The method used to gather the literature

followed the PRISMA framework (Moher et al., 2009), where the literature procedure was split into 4 phases: 1) Identification, 2) Screening, 3) Eligibility and 4) Inclusion, as shown in Figure 4.1.

The findings revealed crucial insights into the current research on group cohesion in TML environments. There is an overreliance on obtrusive measurements, namely the use of surveys, which have known limitations in understanding the complexity of cohesion. In that sense, data and temporal analysis are rare when used to measure and analyse cohesion. Factors that substantiate or influence cohesion in collaborative learning require further study. Most research has been ad-hoc throughout the two decades, with a small build-up of knowledge regarding a topic to an extent. These gaps have quantifiable implications for design and research practice. For instance, the need to produce novel assessment practices using computational and instrument-driven approaches. There is also a need to develop support mechanisms to improve or maintain team cohesion for educational stakeholders, as there are limited tools to achieve this.

8.2 Research aim two: Analytics-based measure for cohesion with temporal motifs

Research aim two was addressed in Chapter 5, where an analytics-based measure was developed to examine the cohesion of teams through their group synchrony using LA approaches. The method addresses the need to use data-driven approaches identified in the systematic literature review by capturing the temporality of cohesion as it occurs in collaborative learning environments. The method applies an analytics-based measure of cohesion using online learner trace data and temporal network motif approaches to understand how cohesion unfolds. For instance, when teams from higher education interact with their learning resources in a work-integrated learning environment. The teams that develop various patterns of synchrony are characterised by their dyadic or triadic interactions within the team over time, impacting their learning performance outcomes differently.

The findings demonstrate that the approach effectively measures cohesion through temporal network motifs. The emerging patterns of team behaviours, their performance, and cohesion were examined. The chapter's findings reveal intriguing insights into how different clusters of teams with emerging learning behaviours and performance are characterised by their temporal network motif groups and their developments. As such, teams with higher instances of triadic interactions, as opposed to dyadic interactions, suggest high levels of shared commitment within the team in achieving their learning goals. Researchers and educational managers alike will find the methodological approach helpful in their collaborative learning settings if they wish to gain insights into the team's cohesion and provide pedagogical support in online platforms.

The analytics-based approach can be implemented in any technological system that captures the logs of team member interactions, including dashboards, to measure group synchrony as a proxy for cohesion. Such an approach allows previously unattainable insights and can positively impact team learning by allowing educators and researchers to monitor and support the cohesion of teams promptly without relying on surveys. The plausibility of the approach is demonstrated in Chapters 5 and 6, which can potentially be used in other learning contexts with similar log data outputs.

8.3 Research aim three: The evolution of cohesive perception in teams and their learning constructs

Research aim three, addressed in chapter 6, aimed to investigate the evolution of team cohesive perceptions over time and its relationship to performance, engagement, group synchrony, and feedback. A flow chart was developed to illustrate the changes in cohesive perceptions over a 3-week course. The method adopted included capturing responses to a task cohesion questionnaire and analysing how

closely the team members' responses matched their peers using a modified IRR agreement. Additionally, an overall task cohesion score for the team was calculated. The findings revealed that teams who evolved to similar cohesive perceptions over the course of the 3-week program had higher cohesion and performance scores than those with different cohesive perceptions. Furthermore, most teams with different cohesive perceptions at the beginning of the program were on par with similar cohesive perceptions by the end.

The insights show that teams with closely aligned cohesive perceptions perform better through their program than those with misaligned cohesive perceptions. Chapter 6 utilised the temporal network motif approach to characterise each cohesive perception based on their motif group developments. The findings indicate similarities in insights, where performing teams and engagement with feedback have more triadic interactions than dyadic ones. Further research and adjustments are required to build construct validity and generalisability to test with collaborative learning environments and cohorts. Nevertheless, using temporal network motifs on how teams interact with their learning content is a promising approach to unobtrusively measuring cohesion.

8.4 Research aim four: Team interactions with learning analytics dashboards

Research aim four was addressed in Chapter 7, where a LAD was developed to capture team interactions in TML to support team cohesion. The LAD was developed using the LATUX framework, and a mixed-method approach was used to test its effectiveness. User engagement and the perceived usefulness of the dashboard were measured through a survey and focus group study. The results showed that the dashboard positively impacted team regulation, workflow, receptiveness, well-being, and psychological safety. Team members and leaders have distinctive roles and behaviours when interacting with the dashboard. These findings are valuable for further developing LADs for teams and customing them based on the needs of

the team's roles. The exciting avenues to improve cohesion and the collaborative learning of teams based on the work in this thesis will be valuable for educational stakeholders in collaborative learning.

8.5 Future work

Based on the findings of research aim one, the following recommendations for future work are proposed: Incorporating artificial intelligence that harnesses data from an LMS based on learner member interactions (Yang et al., 2021) will play a crucial role in monitoring the emergence of cohesion and provide tailored pedagogical support for collaborative learning groups. Increasingly, AI is being used more frequently in pedagogy to provide intelligent support for collaborative learning. For instance, AI can help with automated group formation by placing individual members with complementary skills and knowledge. It can also help with expert facilitation to provide collaborative learning groups with effective problem-solving strategies, as well as intelligent virtual agents that mediate student interactions. Additionally, AI can help with intelligence moderation where the AI agent can help augment and support the collaborative learning of groups through dashboards or informing human tutors to promote cohesion and learning (Luckin et al., 2016).

Several case studies in the systematic literature review promote enabling AI agents to support collaborative learning and improving the cohesion of groups (Terzidou et al., 2016; Yilmaz & Yilmaz, 2019). It is recommended that researchers create environments to support AI systems and foster collaborative learning and cohesion over time. Although, such endeavours are complex and require extensive research and resources. For example, designing technological infrastructure and gathering the 'right' data for the given context to undertake AI in education (Luckin et al., 2016). Therefore, advancing psychometrics in conjunction with LA to collect relevant data that can be referenced is paramount to promoting AI research and providing augmented support.

Given that the existing studies and design implementations to help facilitate group cohesion in TML contexts are very limited, additional studies are required to help advance this area. Researchers in education and teaching must not restrict themselves to in-house literature but explore and take inspiration from other disciplines that have extensively studied team dynamics to facilitate learning, cohesion, and performance experiences. In contemporary sciences, researchers have extensively studied the area of team cognition and learning (Mohammed et al., 2021). There is great potential to utilise ideas across disciplines for an educational context that is highly innovative to advance collaborative learning and cohesion studies in the educational sphere. Based on this review and the gaps identified, researchers are encouraged to enable technologies that help capture, measure, and analyse the temporal development of group cohesion in TML environments. Such approaches will help increase the understanding of the dynamic relationships between cohesion, collaborative learning, and performance and help instructors augment and support the learning of collaborative groups.

Based on the findings of research aims two and three, further research on team cohesion in TML environments can be done to investigate other learning constructs, such as social interactions related to learning, peer-to-peer feedback, physical learning interactions, and proximal behaviours. Social interactions may not be nearly as crucial as task interactions regarding team performance. However, social interactions play an important role in the team's well-being that helps to exercise their communication and collaborative skills, which are pre-cursors for a team's effectiveness. Future work in this area is encouraged to measure the cohesion of teams based on their social interactions instead of task interactions in a collaborative learning environment.

The findings in Chapter 5 can also be leveraged to improve and validate existing or new guidelines that support the training of mentors and clients. The approach will provide quality feedback targeting the team's learning needs, subsequently improving cohesion. A training and learning model to monitor how feedback is improved over time and the effects of team cohesion may be explored for future work and analysis. Future directions require instructors and researchers to enact

team behavioural changes. Support mechanisms need to be developed to identify vulnerable teams. Such approaches will support teams and their cohesion by prompting behavioural changes through feedback that improves their cohesion. It will allow for the continual support of teams with similar cohesive perceptions and improve those with differing cohesive perceptions related to the third research aim. The insights will assist educational stakeholders in changing their educational strategies.

Research aim four has shown that the LAD developed using the LATUX framework (Martinez-Maldonado et al., 2015b) positively impacts team regulation, workflow, receptiveness, well-being, and psychological safety. For future work, it is crucial to consider the teams' overall mindset and health. Monitoring and analysing the synchrony of interactions in the task (i.e., learning interaction) and social (i.e., social exchange) of teams to draw relationships between the two will become an essential undertaking. To do this, it is recommended to use technology such as artificial intelligence (AI) agents and dashboards to monitor and analyse the synchrony of team members' interactions during learning tasks and social exchanges. By drawing connections between these interactions and team performance, educators can identify areas for improvement, such as conflicts or disagreements, coordination issues, or misaligned goals. Instructors in the future will have artificial intelligence (AI) agents and dashboards to help monitor and identify team learning behaviours in learning platforms (Yang et al., 2021). This information can then be used to provide targeted and personalised support to teams, to improve team learning outcomes and cohesion with instructional support (Kim et al., 2020).

In summary, this thesis presents several important contributions to learning analytics and collaborative learning, specifically: the synthesis of existing literature on team cohesion in TML environments, the development of a new analytics-based measure for assessing team cohesion, the characterisation of team perceptions through data analysis, and the implementation of a LAD to support team cohesion in TML environments. These contributions provide valuable insights for researchers and educational stakeholders in the field and offer a starting point for

further exploration of strategies for enhancing team cohesion and collaborative learning in TML settings.

The research presented in this thesis has highlighted the importance of monitoring and analysing team interactions in TML environments to improve team cohesion and collaborative learning outcomes. AI and LADs are recommended to facilitate the monitoring of these interactions in real-time and to provide personalised support to teams. Additionally, we recommend that future research should focus on other learning constructs, such as social interactions related to learning, peer-to-peer feedback, physical learning interactions, and proximal behaviours. Furthermore, implementing SSRL capabilities within the LAD can also provide important insights to educators in identifying team members' motivational, behavioural, and cognitive states, which can be used to provide targeted support to the teams. This research is not only a contribution to the field of learning analytics but also has the potential to support educators and teams in enhancing their collaborative learning experiences in the digital age.

Appendix A

Statement of Authorships

University of South Australia

Statement of Authorship

Title of Paper	The cohesion of small groups in technology-mediated learning environments: A systematic literature review
Publication Status	☑ Published ☐ Accepted for Publication ☐ Submitted for Publication ☐ Unpublished and Unsubmitted work written in manuscript style
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PRINCIPAL AUTHOR

Name of Principal Author (Candidate)	Andrew Zamecnik	
Contribution to the Paper Brief description of your work in this publication	Responsible for data collection, data analysis, research, writing, ethics and editing	
Overall Percentage (%)	65	
Certification	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constr	
Signature *Signatures will be redacted by the Library at the time of publication*	[redacted] Digitally signed by Andrew Zamecnik DN: CN=Andrew Zamecnik, E=Andrew.Zamecnik001@gmail.com Reason: I am the author of this document Location: Home Date: 2023.03.22 19:38:33+10'30' Foxit PDF Reader Version: 12.1.0	Date 3/22/23

CO-AUTHOR CONTRIBUTIONS

By signing the Statement of Authorship, each author certifies that:

I. the candidate's stated contribution to the publication is accurate (as detailed above);

II. permission is granted for the candidate in include the publication in the thesis; and

III. the sum of all co-author contribution is equal to 100% less the candidate's stated contribution.

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CO-AUTHOR CONTRIBUTIONS

By signing the Statement of Authorship, each author certifies that:

I. the candidate's stated contribution to the publication is accurate (as detailed above);

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III. the sum of all co-author contribution is equal to 100% less the candidate's stated contribution.

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Name of Co-Author 8		
% Contribution to the Paper		

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Signature *Signatures will be redacted by the Library at the time of publication*		Date

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Contribution to the Paper Brief description of your work in this publication	Responsible for data collection, data analysis, research, writing, ethics and editing	
Overall Percentage (%)	75	
Certification	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.	
Signature *Signatures will be redacted by the Library at the time of publication*	[redacted] Digitally signed by Andrew Zamecnik DN: CN=Andrew Zamecnik, E=Andrew.Zamecnik001@gmail.com Reason: I am the author of this document Location: Home Date: 2023.03.22 19:38:33+10'30' Foxit PDF Reader Version: 12.1.0	Date 3/22/23

CO-AUTHOR CONTRIBUTIONS

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I. the candidate's stated contribution to the publication is accurate (as detailed above);

II. permission is granted for the candidate in include the publication in the thesis; and

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Appendix B

Survey and focus group questions (For Chapter 7)

B.1 Technology acceptance model (TAM) survey

Ethics application 203250: Technology-Mediated Learning and Assessment of Collaborative Problem-Solving Processes Through Learning Analytics
Internet Survey Questionnaire

- Archival research data related to the Internet Survey Questionnaire was previously collected and conducted from Curtin University
- The data is non-identifiable (anonymised)
- This project requires no recruitment of additional participants / data collected from human participants

The Survey Questionnaire aimed to identify the thoughts of students using a learning analytics dashboard in terms of ease of use and usefulness according to the

technology acceptance model developed by Davis and additional questions related to the dashboard:

- Davis, F. D. (1985). A technology acceptance model for empirically testing new end-user information systems: Theory and results (Doctoral dissertation, Massachusetts Institute of Technology).

The specific questions are as follows:

In your opinion The Challenge Dashboard...

1. Improved my learning
2. Improved my productivity
3. Improved collaboration with my team
4. Monitored team progress
5. Helped process mentor feedback
6. Helped coordinate team's tasks
7. Helped achieve the team's goals

Overall I find The Challenge Dashboard...

1. Useful for my learning
2. Easy to navigate
3. Easy to learn
4. Easy to use
5. Easy to understand

Please rank the proposed functionality by importance

1. Monitoring team workflow progress
2. Setting and organising team goals
3. Comparing progress between team
4. Recommending tasks to team members
5. Visualising team communication

B.2 Focus group questions used for thematic analysis

Ethics application 203250: Technology-Mediated Learning and Assessment of Collaborative Problem-Solving Processes Through Learning Analytics
Focus Group Questions

- Archival data related to the Focus Group Questions was previously collected and conducted from Curtin University that has been transcribed
- The data is non-identifiable (anonymised)
- This project requires no recruitment of additional participants / data collected from human participants

The Focus Group Questionnaire aimed to identify the thoughts of students using open-ended questions that enables a productive conversation with the students to understand their views, such as how a learning analytics dashboard can be significantly improved that is engaging for the next cohort of students to help with their collaborative learning.

Focus Group Questions

1. In what ways did you use the dashboard to help working with your team members?

2. How did you feel using the dashboard? (e.g., frustrated, bored, excited?)

3. Did you find these features useful? (e.g., visuals, tables, interactivity, feedback, filtering and data download options). Can you think of any examples there were useful for collaboration or awareness?

4. Were you motivated to continue using the dashboard? Why or why not?

5. What is your least or most favourite part of the dashboard, and why?

6. Among the visualisations and tables, what did you spend the most time on and why?

7. What support capabilities do you think should be added to the dashboard that would assist in collaborative learning? (i.e. more feed back, helpful pointers?

8. What are the things that you wanted to do with the dashboard that you couldn't? (i.e. set goals for team members and monitor them?)

9. Have you felt any negative feelings such as anxiety, fear, or worry with the dashboard? When did you feel those feelings?

10. Were you able to freely share and express your thoughts, feelings and opinions without any punishment or embarrassment while using the dashboard with your team?

11. What was helpful and what was unhelpful in answering the previous question?

Appendix C

Overview of the Studies Included in the Systematic Review

Table C.1: Publication Timeline and Study Summary

No.	Ref.	Paper Type	Courses	Group Size	Student Pop	Study Duration	Study Type
1	Altebarmakian and Alterman, 2019a	Journal	Psychology	3-4	29	Single Semester	Design Based-Research
2	Altebarmakian and Alterman, 2019b	Conference	Computer Science	3-5	95	Single Semester	Design Based-Research
3	Beranek and Martz, 2005	Journal	Computer Science	3	59	8 weeks	Cross Sectional
4	Bilgin and Gul, 2020	Journal	Technology	3-4	92	13 weeks	Cross Sectional
5	Castro-Hernandez et al., 2015	Conference	Computer Science	5	73	Single Semester	Cross Sectional
6	Castro-Hernandez et al., 2016	Conference	Computer Science	4-5	178	Single Semester	Cross Sectional
7	David et al., 2006	Conference	Computer Science	5	110	Single Semester	Cross Sectional
8	Galyon et al., 2016	Journal	Psychology	3-5	68	Two Semesters	Cross Sectional
9	Garcia and Privado, 2020	Journal	Education	4-5	139	8 weeks	Cross Sectional
10	Gonzales et al., 2010	Journal	Technology	4-5	233	3 months	Longitudinal
11	Guo et al., 2010	Journal	Technology	4-6	324	NA	Cross Sectional
12	Hansen, 2016	Journal	Marketing	4	50	2 years	Cross Sectional
13	Heo et al., 2010	Journal	Technology	7	49	16 weeks	Cross Sectional
14	Lam, 2015	Journal	Technology	3-5	445	NA	Cross Sectional
15	Lu and Xie, 2018	Conference	Education	4-5	171	7 weeks	Cross Sectional
16	Reffay and Chanier, 2003	Conference	Language	4	40	10 weeks	Cross Sectional
17	Reffay et al., 2011	Conference	Language	4	40	10 weeks	Cross Sectional
18	Rogers and Lea, 2004	Journal	Education	3-4	35	4 weeks	Longitudinal
19	Shin and Song, 2011	Journal	Human Resources	3-4	301	Two Semesters	Cross Sectional
20	Tseng and Yeh, 2013	Journal	Mathematics	4	15	15 weeks	Cross Sectional
21	Terzidou et al., 2016	Conference	Technology	2-3	41	1 week	Cross Sectional
22	Wang and Li, 2008	Conference	Technology	4-5	29	Single Semester	Cross Sectional
23	Wang and Hwang, 2012	Journal	Computer Science	3	75	Single Semester	Cross Sectional
24	Wang and Hong, 2018	Journal	Technology	3	96	4 weeks	Cross Sectional
25	Williams et al., 2006	Journal	Management	2-10	300	12 weeks	Cross Sectional
26	Xie et al., 2019	Journal	Education	5-7	171	Single Semester	Cross Sectional
27	Yilmaz and Yilmaz, 2019	Journal	Computer Science	3-5	50	10 weeks	Cross Sectional
28	Yilmaz et al., 2020	Journal	Education	3-5	41	12 weeks	Cross Sectional
29	Zheng, 2017b	Journal	Computer Science	3-4	90	8 weeks	Cross Sectional
30	Zheng et al., 2014	Conference	Technology	4	126	Single Semester	Cross Sectional

TABLE C.2: Definitions, Measures and Analysis

No.	Ref.	Multi-dimensions	Sub-dimensions	Focus of Measurement	Level of Measurement	Level of Analysis
1	Altebarmakian and Alterman, 2019a	Multidimension	Task/Social Cohesion	Mixed	Mixed	Mixed
2	Altebarmakian and Alterman, 2019b	Multidimension	Task/Social Cohesion	Mixed	Mixed	Mixed
3	Beranek and Martz, 2005	Unidimension	Morale	Attitude	Group Level	Group Level
4	Bilgin and Gul, 2020	Multidimension	Belongingness	Mixed	Group Level	Group Level
5	Castro-Hernandez et al., 2015	Unidimension	Task Cohesion	Behaviour	Mixed	Mixed
6	Castro-Hernandez et al., 2016	Unidimension	Task Cohesion	Mixed	Mixed	Mixed
7	David et al., 2006	Unidimension	Morale/Belongingness	Behaviour	Individual Level	Group Level
8	Galyon et al., 2016	Multidimension	Belongingness	Attitude	Individual Level	Group Level
9	Garcia and Privado, 2020	N/A	Task Cohesion	Mixed	Individual Level	Individual Level
10	Gonzales et al., 2010	Multidimension	Group Pride	Behaviour	Mixed	Group Level
11	Guo et al., 2010	Unidimension	Belongingness	Attitude	Mixed	Group Level
12	Hansen, 2016	Multidimension	Belongingness	Mixed	Mixed	Group Level
13	Heo et al., 2010	N/A	N/A	N/A	Mixed	Mixed
14	Lam, 2015	Multidimension	Task Cohesion	Mixed	Mixed	Individual Level
15	Lu and Xie, 2018	Multidimension	Belongingness	Attitude	Individual Level	Group Level
16	Reffay and Chanier, 2003	N/A	N/A	N/A	Mixed	Mixed
17	Reffay et al., 2011	N/A	N/A	N/A	Mixed	Mixed
18	Rogers and Lea, 2004	Multidimension	Belongingness	Behaviour	Group Level	Group Level
19	Shin and Song, 2011	Multidimension	Task/Social Cohesion	Mixed	Mixed	Group Level
20	Tseng and Yeh, 2013	Unidimension	Belongingness	Mixed	Mixed	Group Level
21	Terzidou et al., 2016	N/A	N/A	N/A	Group Level	Group Level
22	Wang and Li, 2008	N/A	N/A	N/A	Mixed	Mixed
23	Wang and Hwang, 2012	Multidimension	Task Cohesion	Mixed	Mixed	Group Level
24	Wang and Hong, 2018	Unidimension	Task/Social Cohesion	Mixed	Mixed	Group Level
25	Williams et al., 2006	Multidimension	Belongingness	Mixed	Mixed	Group Level
26	Xie et al., 2019	Multidimension	Morale/Belongingness	Behaviour	Individual Level	Individual Level
27	Yilmaz and Yilmaz, 2019	Multidimension	Belongingness	Mixed	Group Level	Group Level
28	Yilmaz et al., 2020	Multidimension	Belongingness	Mixed	Group Level	Group Level
29	Zheng, 2017b	Multidimension	Task/Social Cohesion	Mixed	Mixed	Mixed
30	Zheng et al., 2014	Multidimension	Task/Social Cohesion	Mixed	Mixed	Mixed

Table C.3: Environment, Technology and Design

No.	Ref.	Learning Environment	Learning Technology	Design Orientated	Design Detail
1	Altebarmakian and Alterman, 2019a	Blended Learning	Learning Management System	Yes	Homework platform
2	Altebarmakian and Alterman, 2019b	Blended Learning	Learning Management System	Yes	Homework platform
3	Beranek and Martz, 2005	Online Learning	Learning Management System	Yes	Relationship link training
4	Bilgin and Gul, 2020	Blended Learning	Learning Management System	Yes	Exposure to gaming elements
5	Castro-Hernandez et al., 2015	Online Learning	Learning Management System	Yes	Cohesion-related feedback system
6	Castro-Hernandez et al., 2016	Online Learning	Learning Management System	No	N/A
7	David et al., 2006	Blended Learning	Learning Management System	No	N/A
8	Galyon et al., 2016	Blended Learning	Learning Management System	No	N/A
9	Garcia and Privado, 2020	Online Learning	Learning Management System	No	N/A
10	Gonzales et al., 2010	Blended Learning	Learning Management System	No	N/A
11	Guo et al., 2010	Blended Learning	Media Communication	No	N/A
12	Hansen, 2016	Blended Learning	Learning Management System	No	N/A
13	Heo et al., 2010	Blended Learning	Learning Management System	No	N/A
14	Lam, 2015	Blended Learning	Learning Management System	No	N/A
15	Lu and Xie, 2018	Online Learning	Learning Management System	No	N/A
16	Reffay and Chanier, 2003	Online Learning	Learning Management System	No	N/A
17	Reffay et al., 2011	Online Learning	Learning Management System	No	N/A
18	Rogers and Lea, 2004	Online Learning	Media Communication	Yes	Shared social identity
19	Shin and Song, 2011	Blended Learning	Media Communication	No	N/A
20	Tseng and Yeh, 2013	Online Learning	Learning Management System	No	N/A
21	Terzidou et al., 2016	Blended Learning	Agent Based	Yes	Agent to support learning
22	Wang and Li, 2008	Online Learning	Learning Management System	No	N/A
23	Wang and Hwang, 2012	Online Learning	Learning Management System	No	N/A
24	Wang and Hong, 2018	Online Learning	Learning Management System	No	N/A
25	Williams et al., 2006	Online Learning	Learning Management System	No	N/A
26	Xie et al., 2019	Online Learning	Learning Management System	No	N/A
27	Yilmaz and Yilmaz, 2019	Blended Learning	Agent Based	Yes	GAT using pedagogical agent
28	Yilmaz et al., 2020)	Online Learning	Learning Management System	No	N/A
29	Zheng, 2017b	Online Learning	Media Communication	Yes	SSRL mechanism
30	Zheng et al., 2014	Online Learning	Learning Management System	No	N/A

TABLE C.4: Methodological Approaches and Factor Groups

No.	Ref.	Multi-dimensions	Sub-dimensions	Focus of Measurement	Level of Measurement	Level of Analysis
1	Altebarmakian and Alterman, 2019a	Multidimension	Task/Social Cohesion	Mixed	Mixed	Mixed
2	Altebarmakian and Alterman, 2019b	Multidimension	Task/Social Cohesion	Mixed	Mixed	Mixed
3	Beranek and Martz, 2005	Unidimension	Morale	Attitude	Group Level	Group Level
4	Bilgin and Gul, 2020	Multidimension	Belongingness	Mixed	Group Level	Group Level
5	Castro-Hernandez et al., 2015	Unidimension	Task Cohesion	Behaviour	Mixed	Mixed
6	Castro-Hernandez et al., 2016	Unidimension	Task Cohesion	Mixed	Mixed	Mixed
7	David et al., 2006	Unidimension	Morale/Belongingness	Behaviour	Individual Level	Group Level
8	Galyon et al., 2016	Multidimension	Belongingness	Attitude	Individual Level	Group Level
9	Garcia and Privado, 2020	N/A	Task Cohesion	Mixed	Individual Level	Individual Level
10	Gonzales et al., 2010	Multidimension	Group Pride	Behaviour	Mixed	Group Level
11	Guo et al., 2010	Unidimension	Belongingness	Attitude	Mixed	Group Level
12	Hansen, 2016	Multidimension	Belongingness	Mixed	Mixed	Group Level
13	Heo et al., 2010	N/A	N/A	N/A	Mixed	Mixed
14	Lam, 2015	Multidimension	Task Cohesion	Mixed	Mixed	Individual Level
15	Lu and Xie, 2018	Multidimension	Belongingness	Attitude	Individual Level	Group Level
16	Reffay and Chanier, 2003	N/A	N/A	N/A	Mixed	Mixed
17	Reffay et al., 2011	N/A	N/A	N/A	Mixed	Mixed
18	Rogers and Lea, 2004	Multidimension	Belongingness	Behaviour	Group Level	Group Level
19	Shin and Song, 2011	Multidimension	Task/Social Cohesion	Mixed	Mixed	Group Level
20	Tseng and Yeh, 2013	Unidimension	Belongingness	Mixed	Mixed	Group Level
21	Terzidou et al., 2016	N/A	N/A	N/A	Group Level	Group Level
22	Wang and Li, 2008	N/A	N/A	N/A	Mixed	Mixed
23	Wang and Hwang, 2012	Multidimension	Task Cohesion	Mixed	Mixed	Group Level
24	Wang and Hong, 2018	Unidimension	Task/Social Cohesion	Mixed	Mixed	Group Level
25	Williams et al., 2006	Multidimension	Belongingness	Mixed	Mixed	Group Level
26	Xie et al., 2019	Multidimension	Morale/Belongingness	Behaviour	Individual Level	Individual Level
27	Yilmaz and Yilmaz, 2019	Multidimension	Belongingness	Mixed	Group Level	Group Level
28	Yilmaz et al., 2020	Multidimension	Belongingness	Mixed	Group Level	Group Level
29	Zheng, 2017b	Multidimension	Task/Social Cohesion	Mixed	Mixed	Mixed
30	Zheng et al., 2014	Multidimension	Task/Social Cohesion	Mixed	Mixed	Mixed

Table C.5: Statistical Approaches

Statistical Approach	Authors	No.
Regression	Garcia and Privado, 2020; Gonzales et al., 2010; Lu and Xie, 2018, Rogers and Lea, 2004; Wang and Hong, 2018; Williams et al., 2006; Zheng, 2017b	9,10,15 18,24,26,29
Social Network Analysis	Heo et al., 2010; Reffay and Chanier, 2003; Reffay et al., 2011; Wang and Li, 2008	13,16,17,22
Factor Analysis	David et al., 2006; Shin and Song, 2011; Wang and Hong, 2018; Wang and Hwang, 2012	7,19,22,24
T-test	Bilgin and Gul, 2020; Yilmaz and Yilmaz, 2019; Yilmaz et al., 2020; Zheng, 2017b	4,21,29,30
Linguistic Style Matching	Castro-Hernandez et al., 2015; Castro-Hernandez et al., 2016; Gonzales et al., 2010	5,6,10
ANOVA	Hansen, 2016; Williams et al., 2006; Zheng et al., 2014	12,25,29
ANCOVA	Bilgin and Gul, 2020; Terzidou et al., 2016; Yilmaz and Yilmaz, 2019; Yilmaz et al., 2020	4,21,27,28
MANOVA	Beranek and Martz, 2005; Galyon et al., 2016	3,8
Partial Least Squares Analysis	Guo et al., 2019; Lam, 2015	11,14
Levene's Test	Castro-Hernandez et al., 2015	5
Partial Correlation Test	Castro-Hernandez et al., 2016	6
Structural Equation Modelling	Xie et al., 2019	25
Information Exchange Similarity, Rate	Castro-Hernandez et al., 2016	6
Thematic Analysis	Tseng and Yeh, 2013	20

Appendix D

Team Engagement with Learning Analytics Dashboard Poster

Team Engagement with Learning Analytics Dashboards

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1 Introduction

- In this study, a collaborative **Learning Analytics Dashboard** (LAD) was developed to support high school students enrolled in a year-long vocational training course.
- The course is designed to develop their **collaboration** and **problem-solving** skills by working on real-world problems [1].
- In this program, students were using **Challenge**, a web-based learning environment: https://globalchallenge.org.au/Home/about
- The platform is built upon collaborative *problem-based learning* theories
- The goal of this study was to evaluate how students use LAD to monitor and regulate their teamwork and collaborative activities.
- The LATUX design philosophy was implemented for Learning Analytics visualisation [2].
- The LAD captures student interactions with the system (i.e. collecting fine-grained information with the tool).
- The dashboard's design is underpinned by instructional design and learning theory principles

2 Background

Highlights of *several* gaps that remain to be considered in the context of LADs in CSCL contexts:

1. LADs designed for K-12 contexts needs to be further explored to understand how tools enhance teams to regulate their learning in young adults
2. Developing the capability of tracking LADs usage that helps increase our understanding of how students engage with the tool and the connections that can be inferred to their learning behaviours using Learning Analytics (i.e. collaborative learning contexts).
3. Establishing perspectives of students in terms of how dashboards impact their collaborative learning and metacognitive activities

3 Research Questions

RQ1: To what extent did teams use the learning analytics dashboard and how did they interact with those visualisations?

RQ2: How did students perceive the usefulness of the dashboard when gaged in team-based learning?

RQ3: How did students perceive the impact of the dashboard on their collaborative learning experience when engaged in team-based learning?

4 Study Design

- **21** students divided into **8** teams containing **3-4** members per team with a nominated team leader
- **20**-week blended learning environment with active coaching from the instructor
- **3** major deliverables split into **26 tasks** and **91 artefacts** matching specific learning outcomes to obtain their CERT III
- Teams must work together by uploading a draft for a task and improvements to the draft before submitting for assessment
- Each team receives feedback for each artefact submitted that supports the overall learning

5 Methodology

- Designed a LAD using LATUX framework
- Collected fine-grained trace data from LAD
- Conducted Learning Analytics approaches



6 Results

RQ1: Unobjective Results

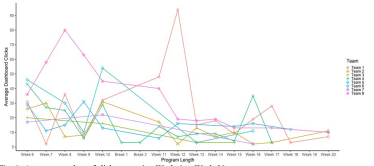


Fig. 1: Average number of clicks spanning Week 6 to Week 20

Team	Role	Team Collaborative Network		Artefact Interaction		Feedback Comments		Artefact Progression		Task Progression		Learning Outcomes	
		Cl	%	Cl	%	Cl	%	Cl	%	Cl	%	Cl	%
Team	Team members	59	49	14	12	12	10	15	13	12	10	8	7
1	Team leader	54	50	5	5	7	6	25	23	8	7	10	9
Team	Team members	26	47	5	9	4	6	16	27	3	5	3	5
2	Team leader	47	72	1	2	4	6	10	15	2	3	1	2
Team	Team members	8	44	0	0	1	6	7	39	1	6	1	6
3	Team leader	22	92	0	0	0	0	2	8	0	0	0	0
Team	Team members	38	46	6	7	6	8	24	28	6	7	4	5
4	Team leader	20	41	1	2	5	10	18	37	2	4	3	6
Team	Team members	28	43	2	2	6	10	24	37	2	4	4	5
5	Team leader	8	40	0	0	1	5	9	45	1	5	1	5
Team	Team members	39	50	13	17	6	7	14	18	4	5	2	3
6	Team leader	15	50	0	0	2	7	12	40	0	0	1	3
Team	Team members	21	51	0	0	3	7	13	32	2	5	2	5
7	Team leader	0	0	0	0	0	0	0	0	0	0	0	0
Team	Team members	131	59	18	8	12	5	38	17	11	5	12	5
8	Team leader	11	85	0	0	0	0	2	15	0	0	0	0
Team	Team members	44	49	7	7	6	7	19	26	5	6	5	5
Avg	Team leader	22	56	1	3	2	5	10	26	2	5	2	5

Table. 1: Total clicks (Cl) and the distribution of clicks (%) with the LADs visualisations by each team leader and team members per team

RQ2 & RQ3: Objective Results

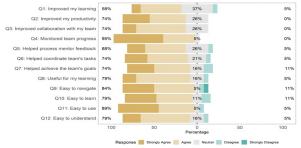


Fig. 2: Survey for perceived usefulness (PU) and ease-of-use (PEOU) of the lad

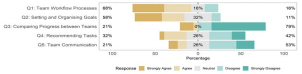


Fig. 3: Additional proposed functionality of the LAD ranked by importance

Focus Group Responses:

Quote 1: *"With the collaboration network, it allowed us to see who was doing what work and how much. So, we all got an equal amount of work or who was working on what so we could help each other out."*

Quote 2: *"There was a lot of data that was sort of like, wow, you know, this really shows us what we've got to change or what we've got to improve."*

Quote 3: *"To be honest, we didn't discuss the dashboard too much with my team, but any conversation we did have about the dashboard, I was able to express my thoughts."*

7 Discussion

- Learning analytics dashboard in K-12 collaborative learning promotes engagement and collaboration
- Collecting trace data from team interactions with a dashboard can be used to support educators and instructors in assessing and improving collaborative learning behaviours
- New interactive visualisations that illustrate workflow processes between members of a team foster higher engagement with the LAD compared to traditional visuals

8 Conclusion

- Discovered insights into behavioural differences between team member and team leader engagement with the learning analytics dashboard
- K-12 teams perceived the learning analytics dashboard as useful in supporting team regulation in collaborative learning settings

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