From Data to Insight: Understanding Students' Metacognition Through Learning Analytics Using Written Reflections and Learning Traces

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Thesis submitted in fulfilment of the requirements for the degree of

Master of Analytics (Research)

under the supervision of
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June 2024

Certificate of Original Authorship

I, Maliha Homaira, declare that this thesis is submitted in the fulfilment of the requirements for the award of Master of Analytics (Research), in the School of Computer Science, Faculty of Engineering and Information Technology at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

This document has not been submitted for qualifications at any other academic institution.

This research is supported by the Australian Government Research Training Program.

Signature: Production Note:
Signature removed prior to publication.

Date: 24 June 2024

Acknowledgements

Reflecting on my academic journey in 2021, during the challenging post-COVID period, when support from supervisors was hard to find, Amara Atif stood out as one of the first to offer her warm support and consistent guidance. From her first response on 21 September 2021 to today, she has always been an exemplary supervisor. After arriving in Australia in 2022, I had the pleasure of meeting Lisa-Angelique Lim, who has been the cherry on top, not just because of her sweetness but for going above and beyond to help, support, and guide me. I feel fortunate to have such a remarkable and outstanding combination of supervisors.

I am also grateful for the President's and International Research scholarships from the University of Technology Sydney. This financial support has been crucial in allowing me to focus on my studies without having the burden of financial stress. I also value the support received from the School of Computer Science.

I sincerely appreciate the valuable feedback and insights provided by Camille-Dickson Deane throughout my candidature assessments. Her guidance has helped me to refine my thesis to a significantly high standard.

It would be remiss of me not to mention Patrick Kelso and Carl Young for providing me with the perfect work-life balance I dearly needed. Their understanding and flexibility allowed me to develop professionally and academically while maintaining my well-being.

I express my deepest gratitude to my parents for their consistent support throughout my academic journey. Lastly, I extend a note of appreciation to my partner, Mahmud Ali, just because he persistently asked me to. Without his relentless reminders, this acknowledgement might have been one line shorter! In all seriousness, thank you, Mahmud.

Research Publications and Academic Presentations

Publications

Homaira, M., Atif, A., & Lim, L. A. (2023, October). Making Sense of Students' Metacognitive Patterns: Analysing Reflections with Epistemic Network Analysis. In International Conference on Quantitative Ethnography (ICQE) 2023.

Homaira, M., Atif, A., & Lim, L. A. (2022, December). Understanding the learning of disabled students: An exploration of machine learning approaches. In 2022 IEEE Asia-Pacific Conference on Computer Science and Data Engineering (CSDE) (pp. 1-6). IEEE.

Presentations

UTS Learning & Teaching Forum. (2023, November 24). Beyond automation: Fostering metacognition through reflections in the age of generative AI. In Shaping the future of learning and teaching. https://lx.uts.edu.au/events/2023-uts-learning-and-teaching-forum-shaping-the-future-of-learning-and-teaching-24-november/

Homaira, M., Atif, A., & Lim, L. (2022). Increasing inclusivity and fairness in learning analytics: Exploring the LMS behaviours of students with and without learning disabilities. ALASI.

UTS Learning & Teaching Forum. (2022, December 2). Summative collaborative learning, a friend, or a foe? Putting the human at the heart of our blended future. https://lx.uts.edu.au/events/2022-uts-learning-and-teaching-forum-putting-the-human-at-the-heart-of-our-blended-future-2-december/

Abstract

Metacognition is a multi-faceted skill that allows students to develop their learning processes effectively. Despite extensive study over the decades, gaps remain in understanding how students employ metacognition in their studies. Leveraging contemporary learning analytics approaches to understand students' metacognitive processes can bridge these gaps and add value to the existing pedagogical practices. This study aimed to explore students' metacognition using data grounded in theory, utilising learning analytics techniques, such as epistemic network analysis, process mining, and natural language processing.

We have examined students' written reflections and metacognitive awareness scores from various IT subjects to analyse differences between high and low-score students' metacognitive processes using epistemic network analysis. Additionally, we employed Linguistic Inquiry Word Count to explore the linguistic features associated with IT students' academic performance and metacognitive awareness. Moreover, we analysed the differences in students' learning traces when metacognitive interventions were applied, using the process mining technique. The intervention involved metacognitive talk time and writing reflections. Data was collected over two semesters from higher education students at the Faculty of Engineering and Information Technology, University of Technology Sydney.

The results indicated no significant difference between high and low-score students' metacognitive processes in their written reflections and metacognitive awareness. However, differences in the distribution of metacognitive phenomena were observed among cohorts from different IT subjects and levels of study. Additionally, students who received the intervention demonstrated varied interactions with the learning content, showing a higher presence of regulatory components of metacognition compared to those who did not receive the intervention. Finally, certain linguistic features, such as personal pronouns, time orientation, tone, emotion, and discrepancy, were significantly associated with students' metacognitive awareness and their academic performance.

This research contributes to our understanding of metacognition in educational practices, highlights the importance of incorporating metacognition into subject design, and identifies possible ways to uncover students' often-hidden metacognitive processes.

Keywords: Metacognition, Learning Analytics, Information Technology, Epistemic Network Analysis, Process Mining, Natural Language Processing

Word Count: 44758

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Chapter 1

Introduction

Effective learning remains a challenge in today's education system. In this dynamic nature of education and fast-paced modern society, it is important for students to have critical and creative thinking, and adopt self-regulated learning (Gibson et al., 2016; Teng & Yue, 2023). One of the most essential skills of this fast-moving 21st century is, without a doubt, metacognition. Metacognition facilitates students acquiring 21st-century skills (Drigas & Mitsea, 2020). Additionally, in this era of Generative AI (GenAI), metacognition is essential as it enables users to effectively understand and plan interactions with the GenAI systems, evaluate the outputs, and adapt strategies to integrate Artificial Intelligence in their workflows (Tankelevitch et al., 2024). Metacognition is an integral part of learning that allows students to monitor and evaluate their understanding, recognise their own cognitive processes, and regulate their learning strategies more efficiently. This enables students to be conscious of their strengths and weaknesses. Based on Flavell's (1976) foundational concept, metacognition was defined as one's own process of thinking about their own thinking. Flavell's (1979) matured concept of metacognition contained four components of metacognition, i.e., metacognitive knowledge (MK), metacognitive experiences (ME), goals (or tasks), and actions (or strategies). Problem-solving, personal development, decision-making, and academic performance are the few areas of our educational and daily aspects of life that metacognition can positively influence (Muijs et al., 2014; Vrugt & Oort, 2008). Many previous studies have proven metacognition as a beneficial factor in academic performance across various learning disciplines (Englert et al., 1988; Romainville, 1994; Schleifer & Dull, 2009).

Reflective writing is regarded as a valuable method for enhancing students' metacognition. It allows students to reflect on their own thinking, which leads to greater self-awareness, problem-solving skills, and a profound comprehension of their own cognitive strategies (Kovanović et al., 2018). Analysing metacognition from students' reflective writing, learning traces, and self-reported questionnaires (e.g., Metacognitive Awareness Inventory, Motivated Learning Strategy Questionnaire, and Learning and Study Strategies Inventories) have been implemented in many previous studies, outlining their effectiveness in the capability of understanding metacognition (Azevedo et al., 2013; Azevedo et al., 2010; Basu & Dixit, 2022; Gibson et al., 2016; Sonnenberg & Bannert, 2016). Thanks to advanced technologies, students' learning data is now easy to access and analyse. The process of gathering, analysing, and delivering significant insights from the learning data is referred to as Learning Analytics (LA) (Siemens & Baker, 2012). Data mining and analytics techniques, such as cluster analysis, epistemic network analysis, sequence mining, process mining, and linguistic feature extraction, are implemented as learning analytics approaches and have been proven effective in understanding students' metacognition (Castro et al., 2023; Cui et al., 2019; Fan et al., 2021; Gibson et al., 2016; Pantić et al., 2022; Wu et al., 2020). The overarching aim of this research was to contribute to enhancing our knowledge of metacognition within the context of higher education in Information Technology settings. The following sub-sections outline the motivation behind this research and research problem (section 1.1), research questions, objectives and contributions (section 1.2), methodologies implemented (section 1.3), and structure of the thesis (section 1.4).

1.1 Motivation and Research Problem

The effectiveness of metacognition is particularly important in computing education due to its demanding nature of tailored learning and teaching approaches (Prather et al., 2020). Students enrolled in Information and Technology (IT) subjects encounter difficulties in comprehending frameworks, concepts, data processing, and analysis to derive meaningful insights and adapt to learning fast-paced technologies. There have been several studies focusing on the role of metacognition in computing education, especially in programming students (Bergin et al., 2005; Eteläpelto, 1993; Dastyni Loksa & Amy J. Ko, 2016; Prather et al., 2020). In contrast to the number of studies performed on computing students' metacognition, there still remains a significant gap in the comprehensive analysis of understanding overarching IT students' metacognition throughout their studies. Additionally, we identified a lack of granular analysis of students' metacognition using diverse learning analytics data sources that were grounded in theory. Addressing this could lead to more effective and timely support to improve students' metacognition.

1.2 Research Questions, Objectives, and Contributions

The overarching aim of this research was to examine IT students' metacognition through the lens of learning analytics, implementing data that are grounded in theory. The primary objective was to use learning analytics to analyse IT students' metacognition, drawing on various data sources, including students' written reflections, event logs, and final scores. These were analysed using statistical and data mining techniques, such as epistemic network analysis, process mining, and natural language processing. This research employed a layered approach to its objectives, research questions, and contributions, organising them hierarchically to explore the overarching aim. The objectives of this research were:

- To explore the differences in high and low-score IT students' metacognition (processes) by examining the distribution patterns of these metacognitive phenomena from written reflections and exploring distinctive differences between these two groups of students in their metacognitive awareness. This analysis did not presume that high-score students demonstrate higher metacognition or vice-versa; instead, it focused on enhancing our understanding of the differences in high and low-score IT students' metacognition.
- To analyse the differences in metacognition between IT students who experienced metacognitive interventions and those who did not, facilitating an understanding of the impacts of the interventions on students' metacognitive awareness and temporal patterns.
- To examine the significant linguistic features that are associated with IT students' metacognitive awareness and their final scores from their written reflections.

From the overarching aim and objectives, several research questions and sub-research questions emerged. The research questions and the sub-research questions are as follows -

- **Research Question 1:** What are the differences between IT students with high and low final scores in terms of their metacognition?
    - **Research Question 1.1.:** How are metacognitive processes distributed in the written reflections of IT students with high and low final scores?
    - **Research Question 1.2.:** What are the differences in metacognitive awareness between IT students with high and low final scores?
- **Research Question 2:** How do semester-long metacognitive interventions have an impact on IT students' metacognition?
    - **Research Question 2.1.:** How do IT students' pre and post-MAI scores differ between students who have experienced metacognitive interventions and those who have not?
    - **Research Question 2.2.:** Are there any differences in the temporal patterns in students' learning traces between IT students who experienced metacognitive interventions and those who have not?

- **Research Question 3:** Which linguistic features in IT students' written reflections are significantly associated with their self-reported metacognitive awareness and final score?

This study collectively contributes to enhancing our understanding of IT students' metacognition. By identifying and understanding the differences between high and low-score IT students' metacognitive processes and awareness, educators can tailor support strategies to improve students' metacognition. Additionally, the insights into the impact of metacognitive interventions on IT students provide valuable information for incorporating interventions into pedagogical practices. Lastly, understanding the linguistic features that are associated with IT students' metacognitive awareness and final scores can support the identification of students who may require targeted interventions.

1.3 Methodology

To answer and analyse our research questions, this study employed a blend of qualitative and quantitative approaches. Data was systematically collected from students enrolled in different IT subjects within the Faculty of Engineering and IT at the University of Technology Sydney, Australia. This data included students' data collected from the institutional learning management systems (Canvas), i.e., event logs, final scores, and students' written reflections. Additionally, a survey was disseminated to the students at the beginning and end of the semesters to analyse their pre and post metacognitive awareness scores. Details of these collected data are outlined in section 3.4. The Metacognitive Awareness Inventory (MAI) can effectively analyse adult learners' components of metacognitive awareness, i.e., knowledge of cognition and regulation of cognition (Schraw & Dennison, 1994). These data sources that were theoretically underpinned ensured a comprehensive analysis of IT students' metacognition. Learning analytics approaches can provide significant insights into students' learning, implementing different data analysis methods to understand the complexity of students' learning (Fan et al., 2021). Following Flavell's (1979) identified components of metacognition, this research employed epistemic network analysis (ENA), using the ENA web tool and natural language processing, using the Linguistic Inquiry Word Count (LIWC) on students' reflective writing. The objectives of implementing these approaches were to (1) understand the distribution of metacognitive phenomena and (2) extract the linguistic features associated with metacognitive awareness and academic performance. Additionally, this research also employed process mining techniques using Schraw's (1994) regulatory components of metacognition to understand the differences in learning traces between students who experienced interventions and those who did not. Different statistical methods were also implemented to understand and analyse the significance. Integrating different learning analytics approaches will give us a comprehensive overview of IT students' complex nature of metacognition.

1.4 Structure of the Thesis

This thesis is comprised of six chapters, organised as follows:

- **Chapter 1: Introduction**

  This chapter provides an introduction to the research, outlining the motivation behind the research and research problem, the significance of this study, presenting the research questions that guided this study, and the methodologies implemented for the analysis.

- **Chapter 2: Literature Review**

  This chapter explores literature related to metacognition in terms of students' learning. This section covers a description of metacognition, including existing frameworks that have been implemented in research. This chapter also discusses the importance of metacognition in the educational context, measures of metacognition, metacognition with learning analytics, and different methods implemented in the study of metacognition (comprehensively discussing the ones implemented in this study).

- **Chapter 3: Methodology**

  This chapter presents the research design this study followed, including ethical considerations, the context of the research, data collection methods, and a comprehensive view of the data analysis performed for each research question.

- **Chapter 4: Results**

  This chapter presents the detailed findings of the research questions after performing data analysis from Chapter 3. The results are organised by research questions, containing tables and figures of the findings.

- **Chapter 5: Discussion**

  This chapter thoroughly discusses the results obtained from the results in chapter 4. It examines the implications of the findings within an educational context and addresses how these findings contribute to the existing knowledge of metacognition.

- **Chapter 6**: **Conclusion, Limitations, and Future Work**

  This chapter provides concluding remarks and limitations of the current study and offers any recommended future work in the area of metacognition.

Chapter 2

Literature Review

This literature review section critically examines the current research and foundational theories related to metacognition in educational settings. The review in the following sub-sections begins by defining metacognition and the related components, the role of metacognition in learning environments, understanding metacognition through learning analytics, outlining measuring techniques and analytical approaches, and ending with highlighting the gaps in the previous literature.

2.1 Understanding Metacognition

Metacognition was first introduced by Flavell (1976), highlighting the concept of "thinking about thinking", making it a significant landmark in cognitive psychology and education. Later, Flavell in (1979) defined "metacognition" as knowledge and regulation about one's own cognitive phenomena. J. H. Flavell (1979) also demonstrated a model of cognitive monitoring that is comprised of metacognitive knowledge, metacognitive experiences, goals (or tasks), and actions (or strategies). Figure 1 represents a visual of the components. In this research, the exact terms (metacognitive knowledge, metacognitive experiences, goals (or tasks), actions (or strategies)) from Flavell's (1979) model were utilised to assure consistency.

Metacognitive knowledge is knowledge or beliefs about one's own cognitive processes. Tarricone (2011) provided a more comprehensive definition of metacognitive knowledge, "Metacognitive knowledge is the accrued long-term knowledge, understandings and beliefs about situations, environments, variables such as person, task, and strategies and sensitivities that interact to affect the representation and outcome of tasks or problems" (p. 129). An example of metacognitive knowledge would be someone having a belief in understanding a concept correctly. Metacognitive knowledge is comprised of three categories – person, task, and strategy. The person category refers to beliefs about oneself or others as cognitive processors. This can be further subdivided into categories - intraindividual (self-belief), interindividual (belief of others), and universals of cognition.

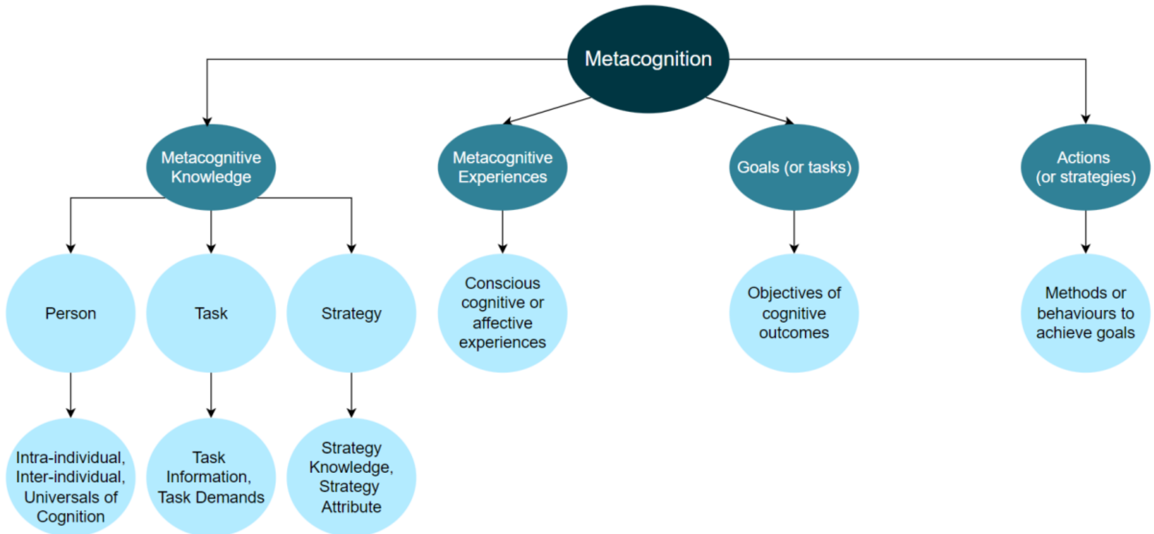


Figure 1: Visual Representation of Framework of Metacognition (adapted from Favell's (1979) and Tarricone's (2011) works)

Intraindividual is the belief about one's own cognitive abilities. An example of this can be a person believing they are better at learning through listening than reading. Interindividual, on the other hand, are the beliefs pertaining to differences between individuals. For instance, recognising that someone else has better memory retention than oneself. Lastly, "universals of cognition" are general beliefs about common cognitive processes shared by all individuals. Examples include understanding attention mechanisms, problem-solving strategies, and metacognitive awareness, which are necessary for learning. Task concerns the available information during a cognitive process. This category includes task information and task demands. Understanding the information available during a cognitive task is task information. Task demands, on the other hand, are recognising the different levels of cognitive efforts or resources required to perform a task. Strategy category refers to the knowledge that can be gained regarding the strategies that are likely to be effective in achieving various goals and subgoals in different types of cognitive activities. This category includes strategy knowledge and strategy attributes. Strategy knowledge involves understanding which strategies are effective for a certain task. For instance, understanding the effectiveness of Mnemosyne for memorising complex information. Strategy attributes are the characteristics and conditions for different strategies, which is simply knowing when and how to apply different strategies. An example can be while performing a complex task, breaking it down into multiple sub-tasks to reduce cognitive load.

Metacognitive experiences, on the other hand, are the inner reactions or insights gained during cognitive activities (conscious processes). An example of this component would be someone feeling difficulty while solving a programming-related task at work. Metacognitive experience can influence metacognitive knowledge and may function as a prompt for goals (or tasks) and tasks (or strategies) (Moritz & Lysaker, 2018). For example, metacognitive experiences can lead to updating existing knowledge, establishing new goals, revising existing ones, and implementing different strategies after an episode of a feeling of difficulty (metacognitive experiences). Thus, metacognitive experience is an integral part of effective learning and problem-solving.

Goals (or tasks) refer to the desired outcome of the cognitive process, guiding individuals on their aims (J. H. Flavell, 1979). For example, feeling difficulty while solving a programming-related task – here, the goal (or tasks) would be setting a new goal to understand the concept behind the task more deeply. In the goals (or tasks) component, both goals and tasks have their interdependence. Goals refer to the desired outcome that individuals aim to achieve. Tasks, on the other hand, refer to the activities to achieve the goal. These terms were used together, which emphasises their close relationship. For example, if a programmer's goal is to debug a complex code, the task would be running use cases and documenting error messages.

Lastly, action (or strategies) is cognition and behaviours to achieve the desired outcome, such as seeking additional help or resources. In Flavell's (1979) component of metacognition, actions (or strategies) are methods and techniques used to achieve the goal. Using both terms together highlights their interconnectedness. Strategies are methods and techniques individuals use to perform a task, and actions are steps taken for these strategies. For instance, to debug a complex programming code, a programmer may isolate the problematic code and break it down to understand each line of code better. Actions in this scenario would be running the debugger to trace and setting the breaking points to understand the errors. This model of metacognition highlights the importance of the interactions among metacognitive knowledge, experiences, goals (or tasks), and actions (or strategies).

Different concepts are interrelated with metacognition. For example, the concepts of metacognition and cognition are often confused as they are interrelated but have differences. Tarricone (2011) clarified their differences, highlighting that while cognition is the activities and information processing, metacognition encompasses the knowledge and regulation of these cognitive processes. Winne (2017) also pointed out the differences, mentioning that "metacognition is cognition about the information input to or output by cognition, as well as information about the operations that work on information. An important feature of metacognition is that what differentiates it from cognition is not the operations involved" (p. 38). An example highlighting the differences can be that reading a textbook is a cognitive activity, while understanding the material, knowing the effective ways to read the book, monitoring study habits, and the strategy implemented to read the book effectively is metacognition. Furthermore, the concepts of metamemory and metacognition are also intrinsically related. Metamemory deals with knowledge and monitoring of memory processes. Nelson (1990) made a contribution to the theory of metacognition and memory by outlining how meta-level and object-level in the memory process are connected. The dynamic interactions between these levels, where meta-level can be represented as "metacognition", is higher order thinking that monitors and controls the object level, which can be expressed as "cognition" (Muijs & Bokhove, 2020; Tarricone, 2011). Figure 2 below highlights the difference and bidirectional relationship between metacognition and cognition. It illustrates how metacognition (the meta-level) interacts with and regulates cognition (object-level). The meta-level (metacognition) controls the object-level (cognition); in turn, the object-level (cognition) provides feedback (monitoring) to the meta-level (metacognition). Tarricone (2011) highlighted that the efficacy of this regulation system depends on the interactions between these two levels.

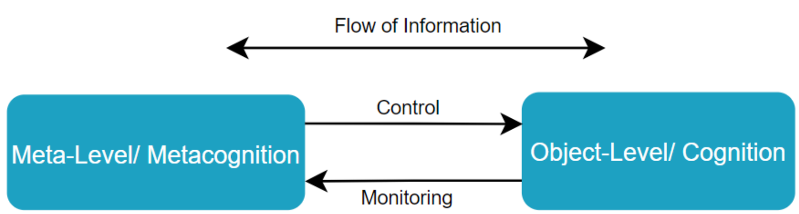


Figure 2: Meta-level and Object-level (adapted from Nelson (1990) and Muijs and Bokhove (2020))

Another concept that is interrelated with metacognition is self-regulation. These two concepts have been researched for decades, but the hierarchical distinction remains unclear. Prather et al. (2020) highlighted that self-regulation is the "process of executing cognitive control during learning or problem-solving tasks" (p. 4). Metacognition, on the other hand, is the knowledge and regulation of cognitive processes. These concepts are researched across various disciplines, leading to inconsistent definitions. This caused some research to consider self-regulation to be a component of "metacognition", and others considered "metacognition" as an element of self-regulation, where the latter viewpoint has predominantly gained acceptance (Muijs & Bokhove, 2020; Prather et al., 2020). Establishing the differences comprehensively was out of focus for this research. However, the interconnectedness of the components highlights the complexity of the cognitive control process.

In previous research, several terminologies developed around metacognition, depending on the study's context (Azevedo, 2020). For example, Quirk (2006) used the term "metacognitive capabilities" in the context of medical education and divided it into two main categories – regulatory strategies and strategic knowledge. Regulatory strategies were described as strategies that "are used to monitor and control thoughts, feelings, and behaviours during a task" (p. 26), and strategic knowledge was divided into declarative, contextual, and procedural knowledge. Aligned with Flavell's (1979) work on metacognition, Efklides's (2006) work on metacognitive experiences suggested two components of metacognition – monitoring and control. Monitoring comprises metacognitive knowledge (beliefs of person, task, strategies, goals, cognitive functions, validity of knowledge, and theory of mind) and experiences (feelings, judgements, and online task-specific knowledge), while control is the metacognitive skills (procedural knowledge - conscious or deliberate activities and use of strategies). Alternatively, Engelmann and Bannert (2021), in their study of self-regulated learning, analysed students' temporal patterns from hypermedia learning and divided metacognition into orientation, planning, goal setting, search, judgement, evaluation, and monitoring. Schraw and Dennison (1994) implemented the term "metacognitive awareness" to assess one's knowledge of cognition and regulation of cognition, as in an earlier study, it was highlighted that aware learners have better performance and are more strategic (Pressley & Ghatala, 1990). Pintrich et al. (1993) used the term "metacognitive strategies" to assess learners' motivation and strategies. Veenman et al. (2000), on the other hand, in their study to analyse the relationship between test anxiety and metacognition, used the term "metacognitive skilfulness".

Metacognitive skill has the ability to develop critical thinking and creative skills, which are necessary skills for the 21st century (Lebuda & Benedek, 2023; Oguz & Ataseven, 2016; Teng & Yue, 2023). Drigas and Mitsea (2020) identified eight pillars of metacognition – (1) academic and theoretical knowledge of cognition, (2) Operational knowledge about the functionality of cognitive abilities, (3) Self-monitoring, (4) Self-regulation, (5) Adaptation, (6) Recognition, (7) Discrimination, and (8) Mnemosyne. Mitsea et al. (2021), later in their study, added "mindfulness" to the list of pillars of metacognition. Table 1 outlines these pillars of metacognition with their definitions. The components of this pillar are interrelated (Drigas & Mitsea, 2020).

Table 1: Pillars of Metacognition (Adapted from Drigas and Mitsea (2020); Mitsea et al. (2021))

Pillars of Metacognition	**Description**
Knowledge of Cognition	It involves understanding mental processes, their operations, and capacities. This foundational knowledge is essential for organising and representing information, which is critical for intelligence and metacognitive development. It includes the abilities to perceive, remember, think, categorise, reason, decide, and feel, with emotions guiding cognitive processes. Theoretical knowledge of cognition is important for training metacognition and supporting the conscious monitoring, regulation, and adaptation of cognitive mechanisms.
Operational knowledge	It involves a practical understanding of how mental tools function in real-world situations. This includes recognising the scope and limitations of cognitive abilities through experience, which is crucial for effective decision-making. It emphasises the importance of applying cognitive skills, understanding their flexibility, and being aware of inherent limitations in cognitive processing, especially in those who do not systematically exercise these abilities. This operational knowledge is essential for adapting and optimising cognitive strategies in various contexts.
Self-monitoring	It involves the ongoing process of observing, assessing, and regulating one's cognitive activities. It includes being aware of and evaluating one's thought processes, strategies, and performance while engaging in various tasks. Self-monitoring helps individuals identify errors, adjust strategies, and improve problem-solving and decision-making. Continuous reflection and adjustment are important for enhancing learning and cognitive efficiency.
Self-regulation	It involves the ability to change, regulate, and fine-tune cognitive abilities as well as mental and emotional states through decisions. This includes the processes of setting goals, monitoring progress, and adjusting strategies and behaviours to achieve desired outcomes. Self-regulation allows individuals to manage their thoughts, emotions, and actions effectively, enhancing their ability to adapt to different situations and challenges. This skill is crucial for maintaining cognitive and emotional balance, optimising performance, and facilitating continuous improvement in learning and problem-solving.
Adaptation	It involves the ability to change the operational status of cognitive abilities to meet work, personal, or social demands. This capability allows individuals to adjust their cognitive processes to be more productive, successful, and happy. It includes modifying strategies and approaches to align with varying requirements and contexts, thereby enhancing overall performance and well-being. Adaptation is essential for effectively navigating different challenges and achieving personal and professional goals.
Recognition	It involves perceiving external phenomena and internal states and operations in their full range and depth. This ability includes understanding cognitive operations and their underlying motivations. Recognition allows individuals to be fully aware of their mental processes and the factors influencing them, facilitating more informed and effective decision-making and problem-solving. This deep awareness is important for

Pillars of Metacognition	Description
	comprehending the complexities of cognitive activities and fostering greater self-awareness and cognitive control.
Discrimination	It refers to the ability to differentiate and distinguish between various cognitive processes, states, and phenomena. This skill involves identifying subtle differences and nuances in thoughts, emotions, and perceptions, enabling more precise and effective cognitive functioning. Discrimination allows individuals to accurately assess and respond to different cognitive and emotional situations, enhancing their overall cognitive flexibility and adaptability. This capability is crucial for fine-tuning cognitive strategies and improving decision-making and problem-solving skills.
Mnemosyne	It refers to the enhancement and utilisation of memory processes (growth mindset). It involves the ability to transform, store, and retrieve information effectively. This pillar emphasises the importance of memory in learning, problem-solving, and adapting to new situations. Memory supports cognitive functions by allowing individuals to recall past experiences and knowledge to inform current thinking and decision-making.
Mindfulness	It involves maintaining acute awareness and attentiveness to the present moment. This includes being aware of one's thoughts, emotions, and sensations without judgment. Mindfulness enhances cognitive processes by promoting focus, reducing stress, and improving emotional regulation. It supports metacognitive development by helping individuals monitor and control their cognitive and emotional states more effectively, leading to better decision-making, problem-solving, and overall cognitive performance.

2.2 Role of Metacognition in Students' Learning and Performance

It has long been recognised that metacognition is important for enhanced learning. In Flavell's work in (1979), he pointed out that "…this area could someday be parlayed into a method of teaching children (and adults) to make wise and thoughtful life decisions as well as to comprehend and learn better in formal educational settings" (p. 910). Additionally, Flavell (1987; as cited in Georghiades, 2004) highlighted that an ideal institution should offer conscious growth. Metacognitive teaching strategy is also essential to develop learners' academic and cognitive performance (Muijs et al., 2014). Metacognition can be developed from an early age. Specifically, the "planning" metacognitive strategy can be developed in learners from ages 10 to 14 (Schraw & Moshman, 1995). Furthermore, Dignath et al. (2008), in their research focusing on primary school children's metacognition, reported that students who were trained on metacognitive strategies developed in motivational aspects (effect size = 0.69), cognitive strategy use (effect size = 0.73), and academic performance (effect size = 0.62). It is also important to note that metacognition can be developed in other levels of learning as well.

For example, Perry et al. (2019) emphasised the need for incorporating metacognition into learning and stated that “Wherever metacognitive skills are taught in lessons, there appear to be improvements in pupil outcomes, irrespective of which subjects are being taught” (p. 489). Additionally, previous research indicated that metacognition not only adds value for primary school-level learners but also contributes immensely to higher education as well. For example, Oguz and Ataseven (2016), in a sample of 520 learners from higher education, reported that metacognitive skills were high in students who were aware of their own consciousness and implemented them effectively, which later developed their critical thinking and self-efficacy skills. In a recent study, Teng and Zhang (2024) investigated how different task-induced involvement loads affect Chinese English as a First Language (EFL) university students’ vocabulary learning and the role of metacognitive awareness in this process. They utilised the metacognitive awareness inventory (MAI) to assess students’ metacognitive awareness. Additionally, the four different tasks that were involved were reading, reading + gap filling, reading + writing, and reading + writing with a digital dictionary. They reported that metacognitive regulation was a crucial predictor of successful vocabulary learning. Metacognition also plays an important role in students’ academic performance; thus, it is necessary to understand the variability of metacognition across disciplines and implement support strategies.

2.2.1 Metacognition and Academic Performance

Metacognition plays an important role in students’ learning outcomes and academic performance. There is substantial research demonstrating that metacognition is positively associated with learners’ academic performance (Coutinho, 2007; Hermita & Thamrin, 2015; Romainville, 1994; Schleifer & Dull, 2009). For example, Pintrich and De Groot (1990) specifically reported metacognitive strategies to be positively related to English performance. Additionally, Wu et al. (2020) implemented Flavell’s (1979) framework of metacognition and analysed high and low-score learners’ metacognition. They reported that high-score students had stronger connections around metacognitive experiences and actions. This finding supports Efklides’s (2006) thoughts on metacognitive experiences, where metacognitive experience was highlighted as an important factor for problem-solving and learning. Furthermore, Englert et al. (1988) also highlighted the importance of metacognition in performance and reported that high-score learners implemented more metacognitive monitoring strategies than low-score learners. Additionally, Young and Fry (2008) and Urban and Urban (2021) highlighted that adult learners can implement metacognitive strategies in a better way. Similarly, Colthorpe et al. (2019) implemented “meta-learning” task assessments on second-year pharmacy students to understand their strategies in self-regulated learning. Meta-learning was highlighted as self-knowledge about one's own learning that includes awareness of learning strategies, behaviours, and attitudes to enhance learning performance (Colthorpe et al., 2017). These "Meta-learning" tasks included questions designed for students to understand their own learning, with identification of strategies divided into phases, i.e., forethought, performance, and self-reflection. They reported that high-achieving students tended to use more forethought and self-reflection strategies, and the quality of these strategies was significantly associated with academic performance. However, Lewthwaite (1996) and Smith and Khawaja (2011) stressed that international students go through several changes, such as new educational settings, cultural environment, and language barriers, which may raise challenges in implementing metacognitive strategies. In contrast, some previous studies have suggested a weak relationship between students' academic performance and metacognition (Gul & Shehzad, 2012; Meijer et al., 2012; Ohtani & Hisasaka, 2018). Thus, it can be inferred that metacognition has a direct and indirect impact on learning. Therefore, understanding and fostering metacognition to enhance learning outcomes across various educational contexts is necessary, which is inadequately addressed in the previous literature.

2.2.2 Metacognition Varies Across Disciplines

Previous studies suggested that cognitive and learning behaviour can be different based on students' disciplines. For example, Aghababyan et al. (2017) reported that between physical/life sciences and humanities/social sciences, students from physical/life sciences demonstrated more confidence, where confidence was considered as a task-specific metacognitive experience. Moreover, Wu et al. (2020) reported that, in students' written reflections, students from natural science demonstrated more fragments of reflections in metacognitive knowledge, but students from humanities disciplines focused more on goals and experiences. As technologies are rapidly changing, it is essential specifically for IT students to learn and adapt to these fast-paced technologies. Along with that, employees in IT roles are required to develop their skills with the evolving characteristics of technology, for companies often rely on self-directed learning (Gravill et al., 2002). Thus, metacognition is essential in learning subjects that fall under the umbrella of information technology. Additionally, metacognition is important as a 21st-century skill for computer science graduate-level students (Zarestky et al., 2022). For example, Zarestky and colleagues implemented flipped classrooms, reflective writing exercises, and student journals to facilitate the development of metacognition. In computing education, Li et al. (2023) examined the impact of metacognition, having a sample of middle school students from computing disciplines, and reported that metacognitive collaborative programming learning (M-CPA) facilitated the development of computational skills, mostly in low-score students. However, Dastyni Loksa and Amy J Ko (2016) highlighted the necessity of students' understanding of the stage they are currently in to enable them to reflect on their process in programming, which is essential for programming learning. Through the examples of previous research, it can be inferred that metacognition differs in terms of students' disciplines; thus, it requires a comprehensive understanding of each discipline's reflective practices and cognitive processes to integrate and support the development of metacognition effectively.

2.2.3 Cultivating Metacognition

Metacognition is trainable. It can be acquired from teachers, peers, and students' cultures, which are all interconnected in metacognitive theories (Schraw & Moshman, 1995). Many previous studies implemented different intervention techniques to enhance students' metacognitive abilities. For example, Thomas and McRobbie (2001) included "metaphor" in the learning process as a metacognitive intervention, which significantly enhanced some students' learning processes. Moreover, Briesmaster and Etchegaray (2017) implemented metacognitive writing intervention in English as a First Language (EFL) students to enhance their coherence and cohesion. In their study, they implemented three stages of intervention, i.e., Pre-writing: planning, During writing: monitoring, and After writing: evaluation. They reported that these EFL students developed in their writing after experiencing the metacognitive intervention, and significant differences were noticed between the experimental and control groups in using linking devices and punctuation marks. Likewise, Sonnenberg and Bannert (2016) implemented metacognitive prompts as an intervention and evaluated the effectiveness of this in a hypermedia learning environment using think-aloud data from an undergraduate human-computer interaction cohort. The metacognitive prompts appeared as a pop-up window that comprised selecting strategic reasons (e.g., orientation, goal specification, planning, control of learning, and monitoring), which popped up several times during a 40-minute learning session. They reported that metacognitive prompts were effective, specifically in monitoring, which was positively correlated with transfer performance. Later, Engelmann et al. (2021) in their study used metacognitive self-created prompts as an intervention with the aim of improving students' learning processes. They reported that even though no significant effect was observed of prompts on learning activities, they found a significant association between prompt utilisation and performance.

Similarly, reflective writing has been demonstrated to be effective in enhancing students' metacognition in different educational contexts.

The concept of metacognition and reflection has similarities (Gibson et al., 2016; Kemmis, 1985). Thus, reflection, e.g., reflective writing, has been implemented in many previous studies as a means of metacognitive intervention. For example, a study by Dignath et al. (2008) on analysing the effectiveness of different training programs and their effect on enhancing metacognitive strategies and self-regulated learning, it was reported that the interventions that were focused on metacognition and metacognitive reflection were more effective than interventions focusing on metacognitive strategies, which had the lowest effect. They have also highlighted that for metacognitive reflection, the highest effect size was found when benefits and knowledge about strategy application were also provided to the students. Furthermore, Wang et al. (2017) analysed the effect of self-reflection on college students' thinking, learning motivation, and self-regulation, where metacognitive strategies were considered under the umbrella of self-regulated learning. They reported that students in the experimental group demonstrated improved thinking, motivation, and self-regulation. Additionally, LaVaque-Manty and Evans (2013) implemented Schraw and Dennison's (1994) regulatory component of metacognition (e.g., planning, monitoring, and evaluation) as an intervention technique to enhance students' learning engagement in undergraduate writing courses (psychology and political science). The intervention technique facilitated the students to improve their writing and reflection strategies. They have also pointed out that their method of intervention was subject-independent and highlighted that "…metacognitive interventions have been a great success. We are convinced they are a valuable tool for increasing students' metacognition." (p. 140). Metacognition is trainable, and intervention or support strategies should be developed by educators to foster this development in students. To effectively integrate support for enhancing students' metacognition, it is essential to understand and establish robust methods for measuring students' metacognition.

2.3 Measuring Metacognition

Measuring students' metacognition is crucial. Even though several methodologies have been developed and implemented over several decades, it is still challenging to measure metacognition (Prather et al., 2020). It is also important to highlight that metacognition is domain-specific (Efklides & Tsiora, 2002; Wu et al., 2020). Jacobse and Harskamp (2012) also pointed out that "the regulation of cognitive activities useful in one domain (e.g. making a summary when reading) may not be directly transferable to another domain (e.g. solving a math problem)" (p. 134-135). However, students' metacognition is being measured using online and offline methods. In online methods, records are captured during a learning process, and in offline methods, data is captured before or after the learning process (Azevedo et al., 2010). The following sections outline a few of the frequently implemented metacognition measuring methods.

2.3.1 Offline Measures of Metacognition

One of the frequently used off-line methods is self-reported questionnaires. Table 2 outlines a summary of self-reported questionnaires that have been implemented to assess metacognition. However, offline measures of metacognition may not capture the ongoing metacognitive behaviour as offline methods are usually delivered before or after a learning task and may have issues with biasedness (Greene & Azevedo, 2010; Veenman et al., 2006). On the contrary, Schraw and Dennison (1994), reported that the self-reported Metacognitive Awareness Inventory (MAI) can measure students' knowledge and regulation of cognition aspects of metacognition. Additionally, Sperling et al. (2002) also highlighted and emphasised that self-reported inventories are less problematic compared to other techniques, as they can be easily implemented and evaluated, allowing one to understand which student may require additional support. One of the most frequently implemented questionnaires to assess metacognition is the Metacognitive Awareness Inventory (MAI). This 52-item questionnaire was developed by Schraw and Dennison (1994) and assesses an individual's awareness of their knowledge of cognition and regulation of cognition. Several studies implemented the MAI to assess metacognitive awareness. For example, Wang et al. (2021) implemented MAI to analyse the effect of metacognition on test anxiety and literacy in students with and without learning disabilities. Their result suggested that for typically developing students, metacognition significantly impacted test anxiety on learning difficulties. Moreover, Basu and Dixit (2022) utilised the MAI to understand the influence of knowledge of cognition and regulation of cognition in different decision-making patterns among 139 MBA students. They reported that knowledge of cognition was positively related to intuitive and spontaneous decisions, and regulation of cognition was linked to rational decision-making style.

Another self-reported questionnaire is the Learning and Study Strategies Inventory (LASSI), developed (1987) by Weinstein et al. (as cited in Kokkinos et al., 2015), which assesses an individual's awareness of the use of learning and study strategies comprised of 80 items. Some studies also implemented LASSI to analyse students' learning and strategies. For instance, the relationship between reading achievement and study strategies in students with learning difficulties and to analyse university students' metacognitive reading and study strategies by implementing LASSI (Bergey et al., 2015; Bergey et al., 2017).

Pintrich and De Groot (1991) developed the Motivated Strategies for Learning Questionnaire (MSLQ), which was designed to evaluate an individual's motivation, cognitive strategies, and metacognitive skills, comprised of 31 motivation-related questions and 50 learning strategies-related questions. Broadbent (2017) used the MSLQ to understand the differences in learners' self-regulated learning when learning in online and blended environments. Additionally, Mokhtari and Reichard (2002), in a 20s study, developed a questionnaire to assess awareness and reading strategies with an aim to improve reading comprehension.

Metacognitive Awareness of Reading Strategies Inventory (MARSI) is another questionnaire that was developed by Mokhtari and Reichard (2002) to assess adult readers' metacognition. A few studies have further utilised this questionnaire, for example, Fitrisia et al. (2015) to analyse reading strategies and Sheikh et al. (2019) to explore the relationship between metacognitive reading strategies and academic attainment.

Table 2: Assessing Metacognition (via offline methods)

Name of Measurement	**Description**	**Examples of implementation in previous studies**
Metacognitive Awareness Inventory (MAI)	Developed by Schraw and Dennison (1994), this questionnaire measures students' knowledge and regulation of cognition aspects of metacognition.	Wang et al. (2021), to analyse the effect of metacognition on text anxiety Basu and Dixit (2022), to understand the effect of metacognition in decision-making
Learning and Study Strategies Inventory (LASSI)	Developed by Weinstein et al. (1987), this questionnaire assesses an individual's awareness of the use of learning and study strategies.	Bergey et al. (2015) implemented LASSI to analyse the relationship between reading achievement and study strategies. Later in (2017), they implemented LASSI to evaluate metacognitive reading and study strategies.
Motivated Strategies for Learning Questionnaires (MSLQ)	Developed by Pintrich and De Groot (1991), this questionnaire evaluates an individual's motivation, cognitive strategies, and metacognitive skills.	Van Vliet et al. (2015) utilised MSLQ to analyse the effects on motivation and strategies during learning in a flipped classroom. Broadbent (2017) utilised MSLQ to analyse the differences in learners' self-regulated learning.

Name of Measurement	Description	Examples of implementation in previous studies
Metacognitive Awareness of Reading Strategies Inventory (MARSI)	Developed by Mokhtari and Reichard (2002), this questionnaire was developed to assess metacognitive awareness and reading strategies among adult readers.	Fitrisia et al. (2015) used MARSI to analyse students' metacognitive reading strategies to increase reading comprehension. Sheikh et al. (2019) used MARSI to understand the association between metacognitive reading strategies and academic attainment.
Reflective Writing	Reflective writing is being implemented to assess students' metacognition through different contexts (see below)	Gibson et al. (2016) to analyse students' metacognitive activities. Kovanović et al. (2018) to develop an analytic system for auto-assessment of reflections. (see the earlier section 2.2.3 for more examples)

Apart from questionnaires, another way of measuring and understanding learners' metacognition offline is through reflective writing. Kemmis (1985) described the nature of reflection as "a dialectical process: it looks inward at our thoughts and thought processes, and outward at the situation in which we find ourselves" (p.141). He also highlighted that "reflection is this 'meta-thinking' (thinking about thinking) in which we consider the relationship between our thoughts and action in a particular context" (p. 141). Gibson et al. (2016) combined the concept of metacognition and reflection in a model with a spectrum from unconscious self to conscious self and used 6090 reflective writings of undergraduate students to analyse the metacognitive activities, demonstrating the model's potential. Moreover, Kovanović et al. (2018) used reflective writing to develop an analytic system for assessing reflective writing, highlighting the importance of reflective writing as a critical factor for developing critical thinking. In this research, we utilised reflective writing as a measure to enhance learners' metacognition. Additionally, MAI was implemented as it's more tailored to assess IT students' metacognition, emphasised by Schraw and Dennison (1994), it can assess adult learners' knowledge and regulation of cognition, and these two components have been implemented in many previous works highlighting their significance (Armbruster et al., 1983; Schraw & Moshman, 1995; Sperling et al., 2002).

2.3.2 Online Measures of Metacognition

Alternatively, online measures of metacognition are also quite frequently used. The advantage of measuring metacognition using online methods is that it can provide real-time data on metacognitive learning behaviour (Jacobse & Harskamp, 2012). These measurements contain data while learners are engaged in a certain learning task. Online measures of metacognition can contain data from students' learning actions, such as taking notes, accessing sources, and clicking buttons (Winne & Perry, 2000). Another online method of measuring metacognition is think-aloud protocols. Data from think-aloud protocols have rich information on students' metacognitive process during a task, and it can be a predictor of academic performance (Schraw, 2010; Veenman & Spaans, 2005). Although gathering and analysing the think-aloud data can be time-consuming and complex, it may not be suitable for assessment for a teaching team without prior experience in using this method (Azevedo et al., 2010). Event log data from students' interaction with the learning management systems is yet another way of measuring metacognition online (Azevedo et al., 2010). Veenman et al. (2004) reported that using log-file along with think-aloud protocols correlated with a score of 0.84. Azevedo et al. (2010) also emphasised the use of think-aloud protocols along with log data. In a later study, Azevedo et al. (2013), in their overview of a hypermedia learning tool, MetaTutor, reported the need to analyse online data, e.g., think-aloud, eye-tracking, note-taking, log files, and facial emotions to capture students' complex cognitive, affective, and metacognitive processes. Moreover, Osakwe et al. (2024), in a recent study, explored different parsing methods and utilised students' trace data to analyse the metacognitive processes to extract meaningful sequences related to self-regulation and cognition. They reported that while trace data provide real-time data of students' learning behaviour, the method of trace parsing influences the identification of the sequences.

Implementing both online (i.e., event logs data) and offline measures (i.e., MAI and written reflections) of metacognition in this study provided a comprehensive view of IT students' metacognition with data that are theoretically grounded. Blending both offline and online measures of metacognition can provide educators with a detailed view of their students' metacognition, allowing them to deliver tailored real-time support to the students. This comprehensive approach underscores the need to use various data sources to understand students' metacognition, leading to the exploration of learning analytics approaches to deepen our understanding of IT students' metacognition.

2.4 Role of Learning Analytics in Metacognition

Previous studies have identified that metacognition can facilitate students' learning. Numerous previous studies implemented learning analytics to analyse and support students' metacognition. Learning analytics was described as "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs." (Siemens & Baker, 2012, p. 252). Learning analytics has made significant progress; however, it is still emerging and has the potential to revolutionise the way students learn (Kandlbinder, 2020). This emerging field offers valuable insights into students' learning, facilitating a deeper understanding of students' learning processes.

One significant aspect of learning analytics is its ability to utilise various types of learning data to gain insights into students' learning and behaviour. Moreover, students' trace data can effectively be implemented to analyse metacognition, as highlighted by Azevedo in (2010) and (2013). Learning analytics was widely implemented to support and enhance students' metacognition. For example, Karaoglan Yilmaz and Yilmaz (2021) reported that university students (enrolled in a Computing course) transactional distance (student-teacher relationship while separated by time) was minimised, and motivation was strengthened after implementing feedback based on learning analytics (was disseminated weekly via the Moodle LMS messaging platform) as a metacognitive tool. In a later study, Karaoglan Yilmaz (2022) reported that this learning analytics-based feedback also increased undergraduate Computing course students' metacognitive awareness, which was measured using the metacognitive awareness inventory and their academic achievement. Continuing with examples, Bodily et al. (2018) implemented a real-time student-facing learning analytics dashboard that included a skill recommender system to enhance university students' metacognitive strategies. However, this perception study did not report any changes in students' metacognition after implementing the recommender system.

Data analytics and data mining are often implemented as learning analytics methodologies. For example, Gibson et al. (2016) analysed undergraduate students' reflections retrieved from a web application called GoingOK to explore students' metacognitive activity and develop an automated extraction system. Their algorithm used a mapping of grammatical features to identify metacognitive indicators. Their algorithm successfully categorised most of the reflections, where 17.6% of the reflections remained undetermined, highlighting the potential of implementing learning analytics to understand students' metacognition. Jovanović et al. (2017) implemented a learning sequence and a cluster of learning sequence analyses to understand undergraduate students' implemented learning strategies. Their study employed students' trace data to identify learning strategies, where only metacognitive control and evaluation were analysed. These learning analytics-based results revealed some significant distinct patterns in students' learning strategies (e.g., high-performing students demonstrated a balanced approach in strategy implementation). In addition to that, Kovanović et al. (2018) implemented LIWC (Linguistic Inquiry Word Count) and Coh-Metrix to create a random forest classification system to analyse features from undergraduate students' reflective writing. In the study, reflective writing was considered an important part of metacognition. Similarly, Fan et al. (2021) implemented a range of learning analytics approaches, i.e., cluster analysis, epistemic network analysis, and process mining, to understand the relationship between learning design and tactics and how these factors influence metacognitive control in a massive open online course (MOOC) setting. They reported that higher-performing groups demonstrated higher regulation, having close alignment on their chosen learning tactics with tasks in the learning design. Azevedo (2020), however, raised concerns about the persistent issue of inconsistent and missing data and ethical concerns.

Although metacognition has been studied for decades, there is a persistent gap in the granular analysis of IT students' metacognition using diverse learning data and analytics approaches that were grounded in theory. To address this gap, we focused on epistemic network analysis, process mining, and natural language processing to gain a comprehensive view of IT students' metacognition. These methodologies are described in the following sections.

2.4.1 Epistemic Network Analysis

Epistemic network analysis (ENA) is a versatile method that was primarily developed for cognitive networks and has the capability to model the patterns of association between information, values, abilities, and other factors of complex thinking, i.e., establishes a relationship between cognitive components (Shaffer et al., 2016). It was developed based on learning analytics principles that emphasised prioritising the interconnectedness of the cognitive elements over merely identifying presence or absence. Learners build expertise by creating a web of knowledge that is a collection of ideas with interconnected links among them (Clark & Linn, 2013). In a similar way, Shaffer et al. (2016) characterised learning as an epistemic frame that characterises associations in communities of practice. The constraints of conventional analysis techniques for structures of connections – (1) the quantity of interactions increases with the addition of elements, making the models with even moderate number of elements demand extensive data, and (2) the essence of the structure of the connection is network-based, where the focus is on the interactions between the model elements, which are often considered as less important than the elements (Shaffer et al., 2016). However, network analysis methods mostly analyse large networks with more than hundreds of nodes (Dorogovtsev & Mendes, 2003). Additionally, the inconsistencies of nodes in the networks lead to an analysis of the data using solely summary statistics, which merely shows the patterns of the connectivity without highlighting the exactly involved nodes (Bowman et al., 2021; Krause et al., 2009). Thus, epistemic network analysis (ENA) comes into the picture, facilitating the analysis of networks that are too large for analysis using multivariate parametric (mathematical models to analyse data that involves multiple variables) yet not too large that they must be solely analysed through summary statistics.

ENA utilises a unique mathematical approach to analyse discourse networks within quantitative ethnography, taking benefits from three key properties – a manageable number of nodes due to the nature of discourse networks in quantitative ethnography, dynamic and variability in the weighted connections that emphasise changes in the weights, and consistency of the discourse elements across contexts (Bowman et al., 2021). Bowman and colleagues also highlighted that this methodology facilitates ENA in providing network representations that offer insights into summary statistics to compare the strength of the connections among the nodes and generate network visualisations that align with the statistics, which ensures consistency between the network graph and the summary statistics. Moreover, Shaffer et al. (2016) highlighted that "Whether ENA is used to model cognitive networks or any other kind of networks, a key assumption of the method is that the structure of connections in the data is most important in the analysis, whether that is the structure of the cognitive connections that students make while engaged in problem-solving, the structure of connections among regions of the brain while participants perform simple tasks, the structure of connections in eye-gaze behaviour when demonstrating a new procedure, or any other context where the structure of connections is meaningful" (p. 12). Considering the significance of the connections among the elements and the limitations of the conventional analysis methods, ENA brings a transformative approach to analysing the cognitive components. The application of ENA in the context of 21st-century learning assessment emphasises performance in complex contexts rather than assessing isolated skills and knowledge (Shaffer et al., 2009). They have also highlighted that ENA can effectively assess learners' performance by mapping and analysing the networked connections among various elements, providing a nuanced understanding of the learning processes and outcomes.

ENA utilises the theoretical framework (discussed above) by highlighting the structure of the connections among the cognitive networks, creating a weighted network of co-occurrences and producing accompanying visuals for each unit of analysis, as explained by Wu et al. (2020). Using this method allows us to accurately visualise the existing nuanced interactions between concepts, beliefs, and skills within the epistemic network. This stanza-based model segments data for analysis and models the relationships between objects. As mentioned by Shaffer and Ruis (2017), stanza-based interaction data includes details on sets of objects and how they relate to one another, providing the connections between them. Several key concepts were also explained: (1) “objects” comprise elements such as a person, people, or concepts of which interactions are being created, (2) “relations” denote the association between objects, (3) “stanzas” represent units in the data, used to measure the interactions between objects and cold steps in a process, (4) “evidence” refer to the exact elements used to identify modelled relationships. To model the network, ENA follows a few steps, illustrated in Figure 3, as demonstrated by Shaffer et al. (2016). Modelling the networks with ENA starts with creating adjacency matrices, and each of these matrices portrays the co-occurrences of codes. Using binary summation, rows that belong to the same stanza based on the codes are combined into a single table (Shaffer, 2018). Step 2 is accumulating these adjacency matrices for each unit in the dataset to create a cumulative adjacency matrix, which reflects the pattern of the weighted co-occurrences. This cumulative matrix, which indicates the strength of association, is a vector in high-dimension space that shows the structure of the connections among different units. The data is normalised in the third step of this process, which is carried out by dividing vectors by their lengths. The idea behind this normalisation is to restrict two vectors from exhibiting identical patterns. Singular value decomposition is employed for dimensional reduction in the final phase to visualise the normalised data.

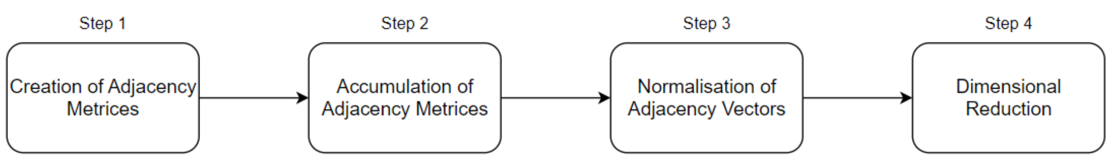


Figure 3: Overview of Step-by-Step ENA Modelling

ENA has been implemented extensively to explore metacognition and other cognitive processes. For instance, Nash and Shaffer (2013) used epistemic frames and epistemic network analysis to examine the relationship between a mentor and a team, Andrist et al. (2018) to model the gaze coordination patterns in a collaborative learning environment, and Bressler et al. (2019) to examine the connections between team roles in a mobile game and their development of collaborative problem-solving by analysis their game conversations. In many other research contexts, ENA was used - Cai et al. (2017) to analyse the conversation data among students to differentiate connections between high and low learning gain students, Fougt et al. (2018) to assess students’ written assignments that support subject learning in formative assessment, and Uzir et al. (2020) implemented three learning analytics techniques. Uzir et al. (2020) combined epistemic network analysis with hierarchical clustering and process mining to understand undergraduate students’ frequency of learning strategies, their connections, and execution time. In their study, they implemented ENA to compute the co-occurrences of learning and time management tactics. ENA, in their study, played a crucial role in providing detailed visuals of the connections between time management and learning tactics. Further examples include - Pantić et al. (2022) to analyse how teachers' understanding towards inclusive practices and Zhang et al. (2022) to explore students' collaborative problem-solving process. Alternatively, Phillips et al. (2023) implemented epistemic frame theory (EFT) and epistemic network analysis to identify Australian and Italian pre-service secondary STEM teachers' patterns of association among knowledge, skills, identities, and epistemologies. Identifying and visualising these patterns revealed unique cognitive differences between individuals and geographical groups. Their study highlighted the need for personalised teacher education and underscored the effectiveness of ENA in identifying tailored needs.

On top of these, ENA has been implemented to understand students' metacognition as well in various contexts. For example, Melzner et al. (2019) implemented ENA to analyse university students' collaborative learning. The students for this study received four vignettes on different self-regulation problems. After reading each vignette, students answered open-ended questions that were coded in strategy types, including metacognitive strategies and social level, which were later analysed using the ENA online tool. Their result indicated that metacognitive strategy had a significant role in students' regulation in collaborative learning. Moreover, Wu et al. (2020) implemented Flavell's framework of metacognition (1979) to analyse the structure of students' metacognitive processes from high and low-score students' written reflections. Additionally, Saint et al. (2020) analysed undergraduate students' self-regulated learning patterns by combining different learning analytics methods, including the epistemic network analysis in a flipped classroom. Their micro-level coding of the trace data included two metacognitive components – metacognitive orientation and metacognitive evaluation. Similar to Uzir et al.'s (2020) and Saint et al.'s (2020) studies, Raković et al. (2023) utilised ENA to analyse the connections between time management and learning strategies and their effects on undergraduate students' academic performance in a flipped classroom. They coded the learning actions retrieved from the clickstream interactions, which included metacognitive evaluation and metacognitive orientation. Furthermore, Fan et al. (2021) also implemented learning analytics techniques that included ENA to understand the relationship between learning design and tactics and how these factors influence metacognitive control in a massive open online course (MOOC) setting. Their results suggested that higher-performing students demonstrated higher regulation, having close alignment on their chosen learning tactics with tasks in the learning design.

In a most recent study, Li et al. (2024) implemented ENA to understand epistemic discourse during collaborative learning. Their coding framework for analysing students' discourse included two primary categories – progressive discourse and metacognition, where metacognition included setting goals, reviewing inquiry, coordinating group efforts, and commenting on ideas.

This research employed this warranted method to explore and compare the distribution of metacognitive phenomena between high and low-score students in their reflective writing, aiming to address the research gap and provide insights into how these two groups of IT students engage and reflect on their learning processes.

2.4.2 Process Mining

Process mining is regarded as a warranted method to analyse students' trace data. Process Mining is a method "to discover, monitor, and improve real processes by extracting knowledge from event logs readily available in today's information systems." (Van Der Aalst, 2012b, p. 1). PM extracts information from the event logs from the information systems and allows the visualisation of the processes within. This workflow mining technology originated from the business community (Van der Aalst et al., 2004). They have also highlighted that process mining can be used as a tool for understanding how procedures work to gain insights into the processes and compare between an actual process and the predefined process. This technique uses event logs from information systems to extract process-oriented insights. Using these logs, PM discovers, monitors, and enhances processes across domains, ensuring process conformance, identifying bottlenecks, and analysing execution issues (Van Der Aalst, 2012a). The focus on process mining has been on analysing business workflow systems and creating Petri net models of these workflows (Van Der Aalst et al., 2007). However, its underlying methods are universally applied to transform event logs into insightful process models. In addition to its implications for business, process mining has been implemented in other domains as well. For example, in the healthcare domain, Kim et al. (2013) used process mining to analyse the outpatient care process to identify further improvements, Mans et al. (2009) to understand the "care flow" of gynecological oncology patients and Suriadi et al. (2014) to analyse the differences in chest pain patients' treatment across South Australian hospitals. This technique was also utilised to understand the software development process (Rubin et al., 2007; Rubin et al., 2014).

In this study, process mining is tailored to the educational domain. Educational Process Mining (EPM) is considered a growing field of study (Bogarín et al., 2018). Bogarín and colleagues also highlighted that "EPM involves the discovery, analysis, and enhancement of processes and flows underlying the event logs generated by virtual learning environments (VLEs)" (p. 2). Thus, EPM has the capability to create process models to understand the behaviour observed and behaviour retrieved from the model. Similar to workflow, studies used the term "learnflows" to convey the same message (Bergenthum et al., 2012). However, there are different types of mining that are related to PM, such as intention mining, sequence pattern mining, and graph mining (Bogarín et al., 2018). Intentional mining focuses on understanding the underlying motive and strategies behind the processes by analysing the event logs, unlike process mining, which aims at constructing sequences of processes using the event logs (Khodabandelou et al., 2013). Sequence pattern mining, however, identifies relationships in the sequences of events to understand any presence of a specific order in which the events may generally occur (Nesbit et al., 2007). Bannert et al. (2014) stressed that sequence pattern mining does not capture all the interconnected processes that might be essential for understanding learners' behaviour. Graph mining, on the other hand, focuses on extracting certain patterns from graphs for classification, but PM uses graphs to create process models of an entire learning process (Bogarín et al., 2018). PM in education focuses heavily on computer science, business, and IT education (Bannert et al., 2014). Thus, it does not illustrate the psychological aspects but rather creates detailed processes of the events. However, PM is still a suggested method as it aligns with the concept of analysing self-regulated learning with event logs (Bannert et al., 2014). Metacognitive and cognitive processes could be analysed using online traces, e.g., timestamps and log file data, emphasising the fact that it is essential to understand the underlying self-regulatory processes (Azevedo et al., 2010).

Many studies have employed process mining in the context of education. For example, Umer et al. (2017) used PM with machine learning techniques to make early predictions of students' learning behaviour in massive open online courses (MOOCs). Hachicha et al. (2021), on the other hand, used the PM technique to learn management systems (LMS) logs to discover and understand process models tailored to an individual's learning needs by extracting event logs and features from the learner's profile. Additionally, Cerezo et al. (2020) utilised PM to analyse the self-regulated learning process during a university-level e-learning subject to identify behaviours and strategies of successful (pass) and unsuccessful (fail) learners. Furthermore, Juhaňák et al. (2019), implementing PM, analysed online quiz-taking behaviour from Moodle LMS data. In a similar study by Tóth et al. (2017), PM enhanced the problem-solving assessment by analysing computer-based assessment data to identify specific problem-solving behaviours. In addition, Dolak (2019) used Moodle logs data in process mining to understand and uncover activities, navigation paths, and behaviours of students enrolled in an e-learning environment at Silesian University. Alternatively, Macak et al. (2021) employed PM to create descriptive models of students' processes to analyse Git logs from students' software development projects to understand and enhance students' learning behaviours and subject outcomes. In addition, Sonnenberg and Bannert (2019) analysed the long-term effect of metacognitive prompts on students' self-regulatory behaviour by using the PM technique. Alongside that, Engelmann and Bannert (2021) examined the impact of metacognitive prompts on students' self-regulated learning behaviour using process mining techniques to understand the influence of these prompts on students' learning sequences. Thus, process mining is being implemented in the education domain to understand students' learning, cognitive, and metacognitive behaviour. However, research on understanding the impact of metacognitive interventions on students' learning traces is still limited.

Figure 4 illustrates the overview of the flow of process mining, which was created and inspired by the work of Bogarín et al. (2018) and Trcˇka et al. (2010) on educational process mining. In the educational environment, e.g., hypermedia, blended, and online learning environments, primary participants are teachers and students. Teachers provide learning materials, and students interact with learning materials (e.g., lectures), activities (e.g., exams), the teaching team, and their peers. The learning management system (LMS) is the platform where the interactions occur. LMS, such as Canvas and Moodle, capture students' interactions and learning actions that occur during a learning process. These captured events are then stored in the raw data format in the databases, which usually are accessible to authorised persons from the institution or organisation. The next stage is applying process mining using different techniques and tools to create process models. Three types of process mining techniques are available in EPM: process discovery, conformance, and extension (Trcˇka et al., 2010). In the process discovery technique, process models are built using the event logs that capture students' learning behaviour and produce observed behaviours. Many algorithms are used for process discovery in the EPM: alpha algorithm (utilises dependency relationships between events, requiring events without noise), heuristic miner algorithm (creates frequency tables and graphs based on event/activity frequencies, also has the capability to deal with noisy and incomplete data), genetic algorithm (creates process models using causal matrices), and fuzzy miner (manages large number of activities and unstructured behaviours) (Bogarín et al., 2018). The conformance-checking technique analyses the discrepancies between observed and modelled behaviours, and the extension technique adds additional information to the process models to enhance the understanding of visible knowledge.

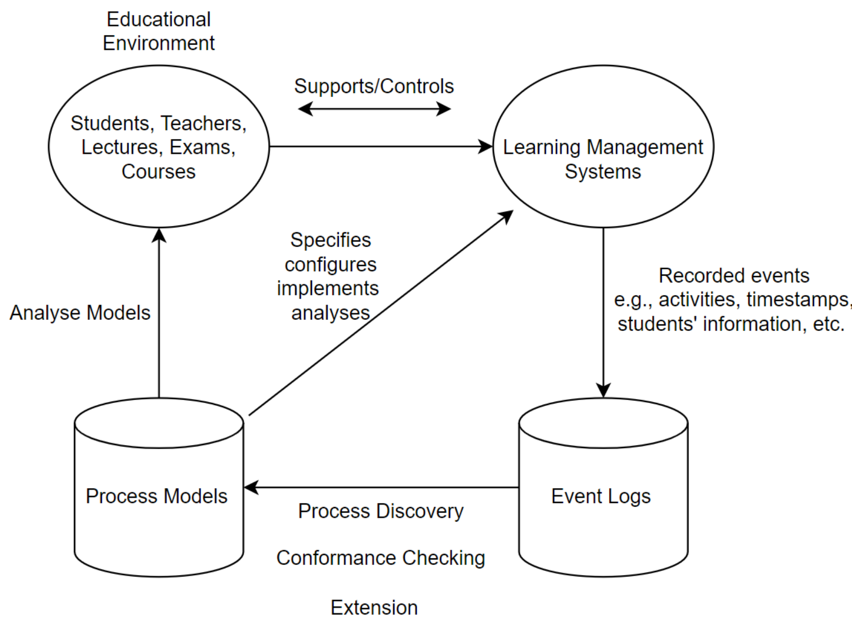


Figure 4: Overview of Process Mining Flow (adapted from Bogarín et al. (2018))

Free and commercial tools, such as ProM and Disco, are available for educational process mining. ProM[1], hosted by TU/e, is free software that allows its users to perform process discovery, conformance checking, and network mining, offering different types of algorithms to perform each process mining technique (Van Der Aalst, 2012b). Disco, created by Fluxicon, is a commercial tool that allows users to perform process discovery techniques using a unique Disco[2] (Fuzzy) miner algorithm (Bogarín et al., 2018; Dakic et al., 2019). Both of these tools are frequently used in educational process mining. In this research, Disco was implemented as it offers to create process discovery models with a more user-friendly interface and allows greater interactivity. Using this educational process mining technique, this research addresses the gap in the existing literature by analysing differences in temporal patterns from students' learning traces and comparing those who experienced metacognitive interventions with those who did not.

2.4.3 Natural Language Processing

Natural language processing (NLP) serves as a method for analysing students' metacognition using textual data. Several NLP techniques have been implemented in studies to analyse and auto-detect students' metacognition. For example, Gibson et al. (2016) highlighted the importance of integrating

[1] For more information on process mining by Tu/e, please visit ProM tools
[2] For more information on automated process discovery by Fluxicon, please visit Disco

metacognition and reflection to foster 21st-century skills in students and developed an algorithm to auto-detect metacognitive activity from students' reflections. Their four-level algorithm in Scala included parts of speech tagging, identifying key phrases, identifying potential annotation, and selecting matched phrase patterns. In their study, they detected metacognitive activity in the "strong", "weak", and "undermined" categories. They highlighted the limitations of their algorithm, noting the need for empirical study with different datasets, potential issues with non-representative datasets used, and challenges associated with the algorithm's performance and accuracy. Huang et al. (2019) also developed an algorithm to detect metacognitive language from online discussion forums implementing NLP automatically. This algorithm was used on 19,700 discussion forum posts from university-level STEM subjects to detect patterns of metacognitive phrases. Their results suggest high accuracy in detecting metacognitive phrases, including a small correlation between academic performance and metacognitive language use. Their study specifically focused on capturing confident and unconfident metacognitive phrases. In a later year, Bosch et al. (2021) implemented NLP to extract and categorise 99 middle school students' statements from interview transcripts while using Betty's Brain, quantifying the frequencies of metacognitive occurrence and understanding their learning behaviour. In their categorisation, they measured only three types – metacognitive knowledge, metacognitive experiences, and strategies, including four metacognitive strategies (i.e., coherent quiz view, mark, edit, read, and feedback). They reported that verbalised metacognition, discovered through NLP, was significantly related to metacognitive strategies. Even more recently, Hutt et al. (2024) performed a comparative analysis between classic NLP techniques and the recent generative AI technique (ChatGPT) to analyse the quality of peer feedback. In this study, peer feedback was considered as an activity that develops learners' metacognitive skills. Classic NLP methods in this research were supervised machine learning algorithms (i.e., tokenisation, parts of speech tagging, random forest, and XGBoost). Interestingly, their results revealed that classic NLP techniques were significantly more accurate than ChatGPT in detecting the quality of feedback. Nevertheless, ChatGPT provided explanations behind its feedback rating.

To analyse students' metacognition from linguistic data, Linguistic Inquiry Word Count (LIWC) is another method/tool that has been implemented in previous studies with its proven validity. Due to its nature of analysing linguistic data, specifically in psychological aspects, this research leveraged LIWC to gain insights into linguistic features that are associated with academic performance and metacognitive awareness. A detailed discussion of this tool and examples of its use are presented in the following paragraphs.

Pronounced as “Luke”, the Linguistic Inquiry Word Count is a software designed for text analysis from written or transcribed verbal text to identify individuals’ psychological states. LIWC, developing and expanding its word dictionaries through the years, enables a comprehensive analysis of psychological states, which include emotions, social aspects, and personalities (Boyd et al., 2022). LIWC enables its users to replicate analysis across various datasets by using the same dictionary, allowing them to make comparisons across different studies (Kennedy et al., 2021). LIWC analyses written or transcribed verbal texts by counting words and percentages that match the dictionary. LIWC also facilitates the creation of users’ own dictionaries based on the context of their research, calculates word frequency and visualisation, performs narrative arc assessment, and matches language style for granular analysis of the texts. This LIWC dictionary has psychologically relevant 117 categories and over 12,000 words, word stems, phrases, and emoticons (Boyd et al., 2022). LIWC’s validity has been supported by many previous studies, highlighting its capability to analyse psychological constructs (Boyd et al., 2022). Each category in LIWC went through rounds of evaluation by three judges, independently rated appropriate words for categories and included or excluded if two or three judges agreed (Pennebaker et al., 2015). Since its first version, the LIWC dictionary has been updated many times (Boyd et al., 2022; Pennebaker et al., 2007; Pennebaker et al., 2015; Pennebaker et al., 2001).

Many studies employed LIWC to analyse the psychological aspects, thus providing its validity. For example, Segerstrom et al. (2003) used LIWC to examine the different styles of repetitive thoughts, using the psychological and emotional dimensions, and analyse their impact on well-being. In a relatively recent study, Lin et al. (2020) used LIWC to examine the linguistic features in online discussions and their effect on the learning outcomes of students in an online Chemistry class, specifically focusing on gender differences and reported that certain linguistic features successfully predicted passing probability. LIWC has also been implemented in many studies in the context of metacognition. For example, Peden and Carroll (2008), considering metacognition as a self-assessment process, used LIWC to understand the linguistic features of self-assessment in academic writing. In recent years, Kovanović et al. (2016), in their study of automated content analysis, used LIWC as one of the techniques to examine the cognitive presence in students’ online discussion transcripts. In a later study, Kovanović et al. (2018) implemented LIWC and examined the linguistic indicators of psychological processes and different types of reflective writing (writing reflection in this study was highlighted to be an essential part of metacognition). In the study, they also emphasised the potential of LIWC in examining students’ written reflections. Moreover, Cui et al. (2019)

examined the written reflections of dental students to analyse the reflective elements and linguistic features that were indicative of metacognition in health professions. In (2023), Castro et al., for example, used LIWC and other natural language processing software for automated content analysis to examine peer feedback (peer feedback in this study was regarded as one of the components that increases self-regulation and metacognition).

The most up-to-date version (LIWC-22) is able to analyse summaries of the features – word count, analytics, clout, authentic, tone, words, big words, and dictionary words. It also facilitates the analysis of 12 primary features – drives, linguistics, cognition, affect, social process, lifestyle, culture, states, physical, motives, conversation, and perception. Through our literature review, we identified that analysis of IT students' writing to identify linguistic features of metacognition is limited; thus, we implemented the warranted LIWC tool to analyse their metacognition.

2.5 Summary

Table 3 outlines a summary of some of the key literature on metacognition, highlighting their metacognition focus, data sources, methods implemented, and the category/groups of students. However, we identified several gaps through our critical analysis of the literature review. Most notably, metacognition from different IT students' educational contexts has not been comprehensively explored. While much research focused on students from primary school to higher education across various subjects, there is limited focus on the metacognition of IT students in higher education across different IT-related subjects. Given the multi-faceted nature of metacognition, students' metacognition can vary from one educational context to another (see section 2.2.2). Therefore, it is essential to specifically analyse metacognition in IT students across different educational settings to gain a deeper understanding of the patterns and the influence of metacognition on their learning. Additionally, previous studies primarily focused on a limited range of data sources to analyse students' metacognition, e.g., students' grades, written reflections, MAI, think-aloud data, learning traces, and peer feedback (see section 2.2 and Table 3). In contrast, this research employed a combination of data that were grounded in theory (i.e., written reflections, final scores, metacognitive awareness scores, and learning traces) to analyse students' metacognition at a granular level. Furthermore, our literature review (until the date of publication of this thesis) indicated that studies have implemented correlation analysis, computational analysis, network analysis, and data mining techniques (see section 2.3 and Table 3) to examine students' metacognition. However, there has been a lack of exploration into a combination of these warranted learning analytics approaches that integrate data that were grounded in theory and analyse metacognition from multiple perspectives.

Thus, this research addresses these gaps and contributes towards understanding IT students' metacognition from different educational settings, implementing learning analytics approaches, i.e., epistemic network analysis, process mining, and natural language processing, and combining the data that were grounded in theory. Additionally, this research not only fills in the existing gaps but also offers potential insights into future studies and implications for incorporating metacognition educational practices. Understanding and tailoring metacognition to different educational settings can facilitate researchers, educators, and education administrators alike, fostering more effective learning approaches.

This chapter reviews existing literature on metacognition, its' role in students' learning, measurement techniques, and learning analytics approaches to identify and address the current gaps. These insights lay the groundwork for future studies and offer practical implications for integrating metacognition in education.

Table 3. Summary of Studies on Metacognition

Author(s)	**Metacognition focus**	**Method(s)**	**Data source(s)**	**Category/group of students**
Englert et al. (1988)	Metacognitive knowledge and its Relationship to learning disabled students' writing performance	Interviews and writing tasks	Interviews using vignettes about students' metacognitive knowledge	260 fourth and fifth-grade students with learning disabilities
Dignath et al. (2008)	Application of cognitive and metacognitive strategies	Differentiated meta-analysis	48 treatment comparisons from 30 articles	Primary school students
Young and Fry (2008)	Metacognitive awareness	Correlation analysis	Metacognitive Awareness Inventory scores, GPA, and end-of-semester grades	133 undergraduate students from Human Learning classes and 45 graduate students from the master's education program
LaVaque-Manty	Metacognitive interventions in writing courses	Quantitative (comparative and statistical) and	Students' written assignments, peer	Advanced undergraduate students

Author(s)	Metacognition focus	Method(s)	Data source(s)	Category/group of students
and Evans (2013)		qualitative (content and thematic) analysis	reviews, and written reflections	in psychology and political science
Oguz and Ataseven (2016)	Relationship between metacognitive skills and motivation	Correlational survey method	Metacognitive Skills Scale to determine students' metacognitive skills and Academic Motivation Scale to determine motivation	520 university students from the Faculty of Education
Sonnenberg and Bannert (2016)	Effectiveness of metacognitive prompts	Data mining and Process mining	Think-aloud data from experimental groups	35 undergraduate students from media communication and human-computer interaction subjects
Gibson et al. (2016)	Reflective and metacognitive competencies	Computational analysis including four algorithms – posTags, phraseTags, subTags, and metaTags	6090 written reflections from GoingOK.1 software	657 undergraduate students
Aghababyan et al. (2017)	Asymmetry in metacognition and changes in students' confidence	Confidence profiling using conditional probabilities, temporal analysis of confidence changes, and correlation analysis with performance	Data from the LearnSmart platform	129,644 students from eight courses (four courses from humanities and four from life/ physical sciences)
Colthorpe et al. (2019)	Self-regulation and Meta-learning	Thematic analysis and Qualitative analysis	Responses from meta-learning assessment tasks	139 undergraduate pharmacy students
Wu et al. (2020)	Metacognitive patterns in collaborative learning	Epistemic Network Analysis	Students' written reflections	87 high-score and low-score university students from Natural science and Human science subjects
Fan et al. (2021)	Metacognitive control and its impact on learning tactics	Cluster analysis, Epistemic network analysis, and Process mining	Interaction logs and performance data from a Chinese MOOC platform	Pre and In-service teachers

Author(s)	**Metacognition focus**	**Method(s)**	**Data source(s)**	**Category/group of students**
Urban and Urban (2021)	Linking self-assessment of creative performance to creative metacognition	Non-hierarchical cluster analysis	Alternative Uses Task (paperclip), Self- and comparative judgments, and Bias Indexes	262 participants from preschool, elementary school, high school, and undergraduate stages
Li et al. (2023)	Improving metacognitive regulation during collaborative learning	Quantitative analysis of the responses from the Likert scale questionnaires	Pre-test, Post-test, Questionnaires on computational and critical thinking, and metacognition	222 third-grade middle school students
Teng and Zhang (2024)	Metacognitive knowledge and regulation	Multiple Regression Analysis and Structural Equation Modelling	Vocabulary Knowledge Scale and Metacognitive Awareness Inventory	150 Chinese university students with English as a foreign language (EFL)
Hutt et al. (2024)	Metacognition in peer-feedback	Natural language processing and large language model (ChatGPT)	Peer feedback from CueThink platform	203 Middle school students from grades 6-8

Chapter 3

Methodology

This section outlines the methodological approach employed to conduct the research, with details on research design, ethical considerations, research context, data collection, data preparation and processing, and analysis methods implemented.

3.1 Research Design

Figure 5 illustrates the implemented research design inspired by Saunders et al. (2015) research philosophy and theory development model (the "research onion" model). Refer to section 1.2 to review the research questions that are discussed in this research design. The ***philosophy*** behind this research is - Interpretivism and Pragmatism. Interpretivism, in this study, was selected because it allows for understanding the phenomena from the perspective of the participants involved, exploring the subjective experiences, beliefs, and perceptions of students regarding their own cognitive processes and strategies. Pragmatism complements this by ensuring that the study not only involves understanding the theoretical concepts of metacognition but also seeking practical applications and instructional strategies. The ***Approach to theory development*** for this study was the deduction method for all research questions because each question aimed to test existing theories and frameworks in a specific context, thus building on well-established concepts such as Flavell's (1979) components of metacognition and Schraw and Dennison's (1994) regulatory components. This method was preferred over an inductive approach, which would have required generating new theories, as the study's primary goal was to test and apply existing theories to specific data sets. For instance, RQ1.1 relied on the deductive approach to analyse the distribution of metacognitive phenomena based on established frameworks in high and low-score students. The decision to use Epistemic Network Analysis was made because it allowed for a structured analysis of reflective writing, in line with Flavell's components of metacognition. Alternative methods, such as grounded theory or thematic analysis, were considered, but these would have required more open-ended exploration without the necessary alignment with predefined theoretical constructs. Similarly, RQ1.2 and RQ2.1 followed the deductive approach, as previous studies already reported the association between metacognitive awareness and academic performance, as well as interventions. This approach ensured the study remained grounded in established knowledge, increasing the reliability of the analysis. Process mining was chosen for RQ2.2 to explore temporal patterns in student behaviours, as it provides a dynamic view of the data, something that static methods such as regression analysis could not achieve. Lastly, RQ3 was a deductive approach as it involved analysis of the linguistic features in students' written reflections and their associations with students' metacognitive awareness and academic performance, using the Linguistic Inquiry Word Count approach where mapping of specific linguistic features was performed utilising Flavell's (1979) framework. The ***methodological choice*** for this study was "mixed method simple", which incorporated both quantitative and qualitative data. A simple mixed method was chosen rather than more complex designs (such as explanatory sequential design) to maintain clarity and efficiency in analysing different types of data. For example, for addressing RQ1, quantitative data, e.g., metacognitive awareness scores and academic performance scores and qualitative data, e.g., students' written reflections, were utilised for analysis. For RQ2, quantitative data (e.g., metacognitive awareness scores and events logs) was utilised for analysis. For addressing RQ3, both quantitative and qualitative data (e.g., students' written reflections, academic performance, and metacognitive awareness scores) were used. In terms of ***strategies***, this research followed – a Survey and Case study. Survey - as data was collected using the metacognitive awareness inventory as a survey to analyse students' metacognitive awareness. This was paired with case study analysis which allowed for a (1) in-depth examination of differences in metacognitive phenomena in high and low-score students (RQ1), (2) differences in temporal patterns were analysed for a cohort of students who experienced metacognition, and those who did not (RQ2), and students' significant linguistic features in students' written reflections and their associations with students' metacognitive awareness and academic performance was performed dividing the students into four quartile groups (RQ3). Alternative approaches, such as experimental designs, were considered but deemed less suitable, as the focus was on naturalistic observation of students' behaviours rather than controlled manipulation of variables. The ***time horizon*** for this research was a cross-sectional study as data was collected from a single point in time during the Autumn and Spring 2023 sessions. A longitudinal approach was not chosen due to constraints in tracking students over an extended period. Finally, the ***techniques and procedures*** for data collection and analysis are discussed in the following sections.

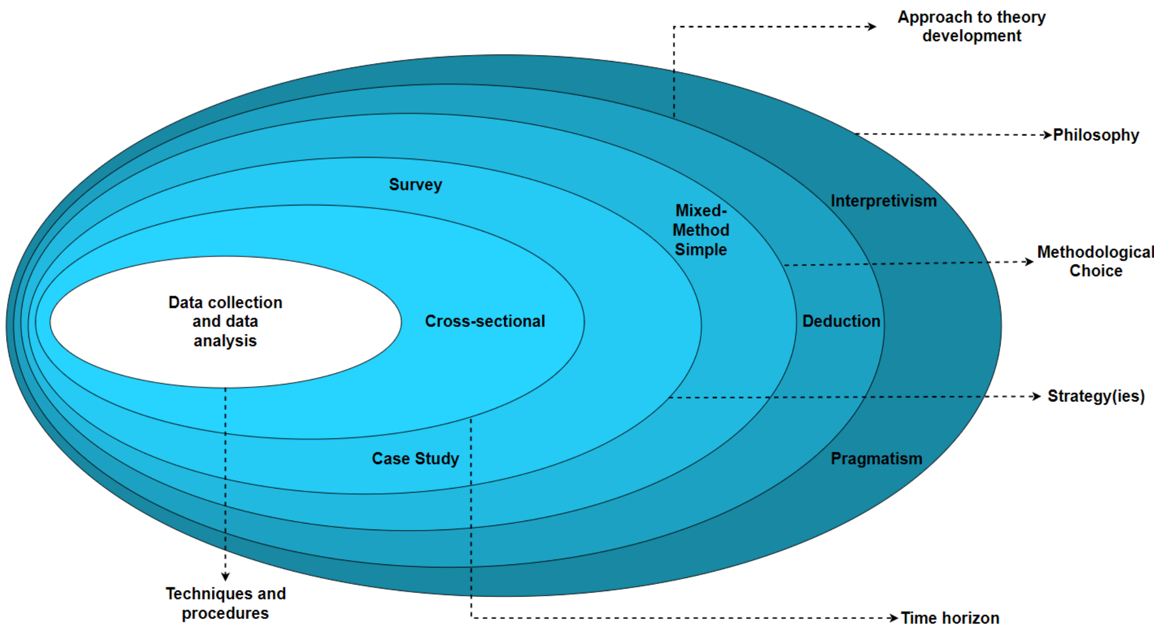


Figure 5: Overview of the Research Design (based on Saunders et al. (2015))

3.2 Ethical Considerations

Ethical considerations were carefully considered throughout this study to ensure they met human research standards and University of Technology Sydney (UTS) policy and guidelines, with an approval number UTS HREC REF NO. ETH23-7893. Ethics approval was obtained from the research office before the data collection process was commenced. Participants received an outline of the purpose of the study and were informed of their rights to withdraw at any time without consequences. All data collected were stored securely and only analysed by researchers involved in this study. Additionally, the anonymity and confidentiality of the collected data were upheld by removing any identifiable information available and using a secure data storage method. A copy of this study's research data management plan is available in Appendix A. Only data from students who consented to participate was utilised throughout the study using pseudo-IDs for reference. The study's ethical procedures were regularly monitored to address any emerging issues, ensuring alignment with the outlined activities stated in the approved ethics document. A copy of the ethics approval is available in Appendix B.

3.3 Research Context

The data collection was carried out during the Autumn and Spring 2023 sessions at the Faculty of Engineering and Information Technology (FEIT), University of Technology Sydney, Australia. At FEIT, one of the emphasised graduate attributes is "reflectiveness"[3], which aligns closely with the focus of this research on metacognitive processes in educational settings. This attribute highlights the faculty's commitment to developing students' abilities to reflect on their actions and learning processes, which is central to the study's objectives. An invitation to participate was extended to all undergraduate and postgraduate subject coordinators within the School of Computer Science, FEIT, during the specified sessions. To maintain confidentiality and ensure the anonymity of the subjects involved, actual subject codes and names were not used to report the data. Instead, alphanumeric subject codes were employed, which indicate only the discipline (represented by the first two letters) followed by a hyphen and a digit that signifies the unique subject code.

Table 4 outlines the subjects that were on board for this study. In Autumn 2023, three subject coordinators from IT-01, IT-02, and IT-03 subjects consented and expressed interest in participating in the study. Due to insufficient data retrieved from Autumn 2023, a second round of data collection process was conducted in Spring 2023. Two subject coordinators from three subjects, IT-04, IT-05, and IT-06, expressed their interest and participated in the study. Despite the IT-06 and IT-03 subject coordinators' generous offer to participate, this study excluded these two subjects from the analysis as no student responses were received (highlighted in the orange-red shade in Table 4). From these two sessions, four subjects were on board – two undergraduate IT subjects (IT-01 was 4th year and IT-02 was 1st year) and two postgraduate IT subjects (IT-04 and IT-05 had a mixture of 1st and 2nd-year students).

[3] University of Technology Sydney. "Graduate Attributes and Engineers Australia Stage 1 Competencies". Click here to read more about the attributes.

Table 4: Overview of the subjects providing the contexts for this research

Subject	Data Collection Time period	Mode of Delivery	Level of Study	Enrolment Size	Subject Focus	Responses Received (see section 3.4 below for details)
IT-01	Autumn 2023	Blended	Undergraduate	31 students	Business and IT-related content	Yes
IT-02	Autumn 2023	Blended	Undergraduate	Over 600 students	Introductory programming-related content	Yes
IT-03	Autumn 2023	Blended	Undergraduate and Postgraduate	70 students	Design studio-related content	No
IT-04	Spring 2023	Blended	Postgraduate	97 students	Business and IT-related content	Yes
IT-05	Spring 2023	Blended	Postgraduate	225 students	Business and IT-related content	Yes
IT-06	Spring 2023	Blended	Postgraduate	173 students	Business and IT-related content	No

3.4 Data Collection Methods

As discussed in the previous section, data was collected over the Autumn and Spring 2023 sessions. During these sessions, four types of data were collected and securely stored of students who consented to participate in the study: students' self-reported Metacognitive Awareness Inventory (MAI) survey responses, event logs from Canvas Learning Management Systems, students' final scores (not grades) in the subject, and students' written reflections (see section 2.3.1 and 2.3.2 to understand the rationales behind the collected data). In both semesters' data collection processes, the MAI survey was distributed to the students at the beginning of the semester in week 3 (referred to as Pre-MAI) and at the end of the semester in week 10 (referred to as Post-MAI). IT-01 had a cohort of 30 students, where 27 students consented to participate, and IT-02 had a cohort of over 600 students, where 33 students consented to participate in the study in both pre and post-MAI surveys. Of the 99 students in IT-04's cohort, 40 consented to participate, and 16 students (out of 256 students) in IT-05's cohort consented to participate in the study in pre and post-MAI surveys. Figure 6 illustrates the data collection flow followed for the Autumn 2023 session, and Figure 7 illustrates for Spring 2023 session. From Figure 6 and Figure 7, in week 3 and week 10, students received the Metacognitive Awareness inventory to self-assess their metacognitive awareness at the beginning (pre-MAI) and end of the semester (post-MAI). It is important to note that while students from all four subjects received both pre and post-MAI surveys, students from IT-01 and IT-04 experienced metacognitive interventions (Metacognitive talk time and Reflection writing) throughout the semester. For both Autumn and Spring 2023 data collection, canvas event logs and students' written reflections data were collected throughout the semesters (see Figure 6 and Figure 7). However, due to a lack of technical equipment in the class, the metacognitive talk time data could not be stored and, thus, was not analysed for this study. Students' final scores were downloaded from the Canvas LMS at the end of the semester (see Figure 6 and Figure 7). The following sub-sections provide comprehensive details of the four types of data collected in both the autumn and spring 2023 sessions **-** ***Survey Data***: students' self-reported Metacognitive Awareness Inventory (MAI) survey responses, ***Logs Data*****:** event logs from Canvas Learning Management Systems, ***Final Scores from Canvas*****:** students' final scores (not grades) in the subject, and ***Students' written reflections***.

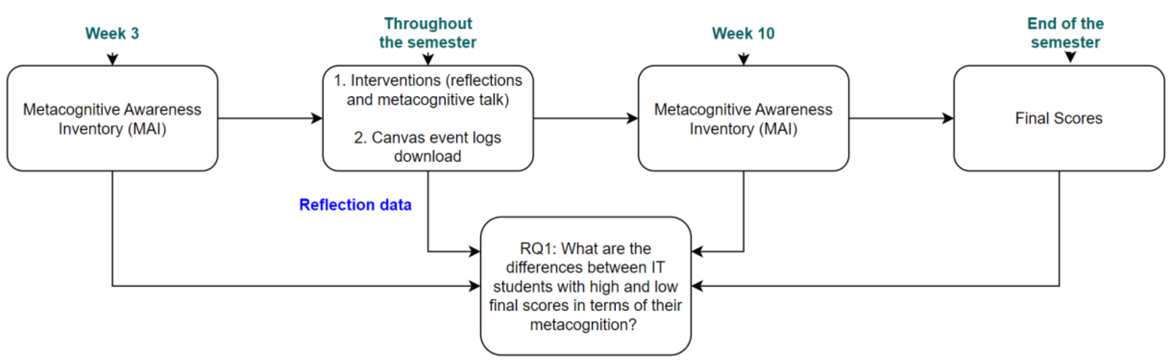


Figure 6: Autumn 2023 Data Collection Flow for addressing RQ1

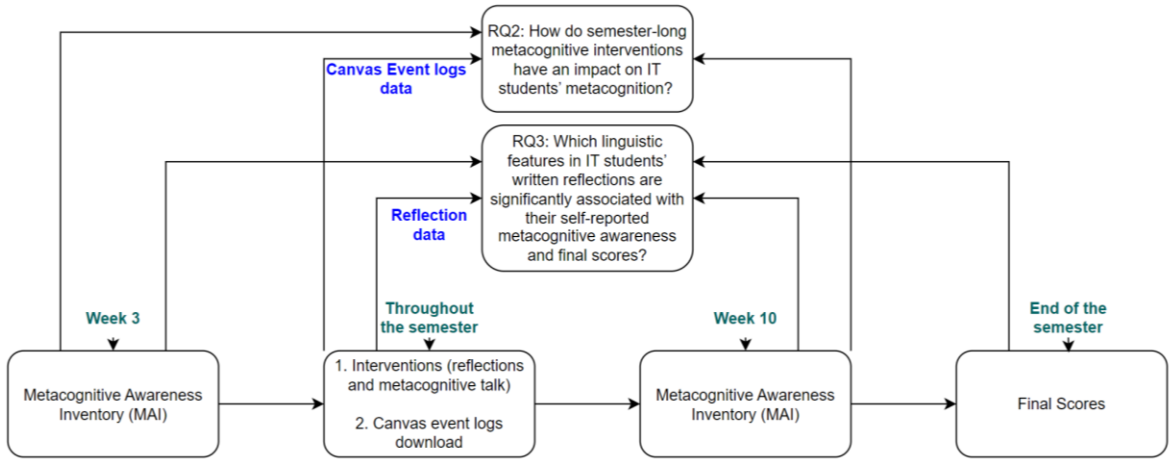


Figure 7: Spring 2023 Data Collection Flow for addressing RQ2 and RQ3

3.4.1 Survey Data

The Metacognitive Awareness Inventory (MAI) survey was designed using Qualtrics software (Qualtrics, 2023) and disseminated to the students via the university's Canvas Learning Management Systems (LMS). While disseminating the MAI surveys, students were provided a concise overview of metacognition, its significance, and guidance on completing the questionnaire. To ensure adequate time to complete the inventory and precisely capture learners' metacognitive awareness scores at the beginning (referred to as Pre-MAI) and end of the semester (referred to as Post-MAI), the availability timeframe was carefully assessed in both the Autumn and Spring 2023 sessions. For Autumn 2023 data collection, the pre-MAI survey was distributed on Week 3 and was available from 4 March 2023 to 26 March 2023. The post-MAI survey was disseminated on Week 10 and was available from 1 May 2023 to 15 May 2023. Alternatively, Spring 2023's pre-MAI (Week 3) survey was distributed on 14 August 2023 and was available until 10 September 2023. Post-MAI (Week 10) survey was available from 19 October 2023 to 20 November 2023 in Spring 2023.

The metacognitive awareness inventory (MAI) was implemented in this study to measure students' awareness of metacognition. It was developed by Schraw and Dennison (1994), and it has proven valid in assessing learners' knowledge of cognition and regulation of cognition (see section 2.3.1 for examples of usage). This metacognitive awareness inventory contains 52 questions, satisfying a total of 8 subcomponents – knowledge of cognition (declarative knowledge, procedural knowledge and conditional knowledge) and regulation of cognition (planning, information management, monitoring, debugging, and evaluation). The distribution of these 52 questions varied across the subcomponents: declarative knowledge (8 questions), procedural knowledge (4 questions), conditional knowledge (5 questions), planning (7 questions), information management (10 questions), monitoring (7 questions), debugging (5 questions), and evaluation (6 questions). The instrument implemented in this study used a five-item Likert Scale response format starting from – *I "never" do this* to *I do this "always"* adopted from previous studies (Akin et al., 2007; Harrison & Vallin, 2018), to allow for more fine-grained analysis. Students received this questionnaire at the beginning and end of the semester (as earlier illustrated in Figure 6 and Figure 7). This data was utilised to address RQ1, RQ2, and RQ3. A copy of the survey is available in Appendix D (Pre-MAI) and Appendix E (Post-MAI). Additionally, a description of the components with their examples is outlined in Table 5.

Table 5: Components of Knowledge of Cognition and Regulation of Cognition

Primary Components of Metacognitive Awareness	**Sub-Components of Metacognitive Awareness**	**Description**	**Examples from the "Metacognitive Awareness Inventory"**
Knowledge of Cognition	Declarative Knowledge	Knowledge and understanding of one's own abilities, intellectual resources, and skills as a learner	"I am good at organising information."
	Procedural Knowledge	Knowledge and understanding of "how" to implement certain strategies	"I have a specific purpose for each strategy I use."
	Conditional Knowledge	Knowledge and understanding of "why" and "when" to implement certain strategies	"I learn best when I know something about the topic."
Regulation of Cognition	Planning	Allocating resources and setting objectives before learning	"I think about what I really need to learn before I begin a task."
	Information Management	Techniques and strategy sequences implemented for processing information	"I slow down when I encounter important information."
	Monitoring	Assessing one's own learning or the strategies implemented	"I ask myself periodically if I'm meeting my goals."
	Debugging	Strategies implemented to correct understanding and performance	"I ask others for help when I do not understand something."
	Evaluation	Reviewing and analysing the effectiveness of the strategies implemented after a learning session	"I ask myself how well I accomplished my goals once I am finished."

3.4.2 Logs Data

Students' event log data was downloaded from the Canvas learning management systems (LMS) on a biweekly basis from the "New Analytics"[4] feature of Canvas. This approach was carefully maintained, adhering to the university's canvas event logs data policy. This policy allowed only the download of the event logs of the past two weeks, after which the data was no longer available to download. This biweekly download of Canvas event logs allowed us to capture students' most recent event logs. The downloaded data were securely stored in authorised sites and devices, with access only to the researchers of this study. This raw data contained student canvas ID, student ID, student name, section name, section ID, course ID, type of content viewed, how many times a student viewed and participated in a specific content, start date, and first and last view of a particular content However, the data was later processed to contain event logs of students who consented to participate in both pre and post-MAI surveys. This data collection followed a strict procedure to maintain confidentiality. Any identifiable information was replaced with a pseudo-ID. This data was utilised to address RQ2.

3.4.3 Academic Performance (Final Scores)

Students' final scores (not letter grades) were downloaded from Canvas LMS at the end of the semester after the subjects' scores were finalised. The final scores provided a quantitative measurement of students' academic performance. This data contributed to the analysis of – high and low-score students' differences in metacognition (RQ1) and the significant linguistic features associated with students' academic scores (RQ3). This data collection followed a strict procedure to maintain confidentiality. Any identifiable information was replaced with a pseudo-ID. Similar to the event logs, this data was later processed to contain the final scores of students who consented to participate in both pre and post-MAI surveys.

3.4.4 Students' Written Reflection Data

Weekly reflections and metacognitive talk time were a part of the metacognitive intervention. As mentioned in the earlier section, the metacognitive talk time data could not be stored and analysed due to insufficient technical equipment. However, this section highlights the unique process followed for the interventions and how data on students' written reflections was collected. Students who received metacognitive interventions (IT-01 and IT-04) followed a uniform approach for the

[4] "New Analytics" feature of Canvas provides detailed data and reports on subject grades, student participation, activity logs, and other metrics.

interventions. The subjects were administered in the Canvas learning management system, where students engaged in various activities designed to enhance their learning experience. At the heart of this approach were the weekly tutorials, which were structured into three distinct components to foster a holistic learning environment:

(1) Collaborative tasks - students participated in collaborative tasks aimed at promoting teamwork, problem-solving skills, and knowledge sharing among peers. These activities involved group discussions and content-specific interactive tasks that encouraged active engagement with the subject material.

(2) Metacognitive talk time (discussion session) - a dedicated portion of each tutorial was allocated to "metacognitive talk time", providing students with an opportunity to present their answers to questions to the class, reflect on their learning processes, discuss their cognitive strategies, seek/provide feedback from/to their peers, and articulate their understanding of the subject matter. These discussions likely encouraged students to evaluate their own thinking processes and monitor their learning effectively.

(3) Weekly reflection questions - students were presented with weekly reflection questions that prompted them to critically evaluate their learning experiences and apply metacognitive principles to their studies. These questions were closely aligned with the subject content and were designed to stimulate deep reflection on key concepts and learning outcomes. Data for this study were collected from two sources: students' written reflections and the Metacognitive Awareness Inventory (MAI), developed by Schraw and Dennison (1994). Data from students' written reflections was collected weekly (Week 1 until Week 10). Details of this task are outlined in the following paragraph.

Weekly reflection questions were customised for every week depending on the learning content of the period. For example, in a weekly learning content on prescriptive analytics, the reflection questions were, "What resources did you use while working on the tutorial questions related to prescriptive analytics? Which resources were especially helpful? Which resources would you use again?". Clear guidelines and prompts were provided to support students in developing their metacognitive abilities through reflective writing. These guidelines emphasised the importance of incorporating specific elements into their reflections, such as providing examples and evidence from their learning experiences, articulating their thought processes, discussing challenges encountered, describing strategies employed, reflecting on any adjustments made in their approach, and identifying actionable insights for future learning endeavours. By incorporating reflective writing and metacognitive talk time into the instructional design, the aim was to empower students to become more self-aware students, capable of monitoring and regulating their cognitive processes effectively. Additionally, providing explicit guidance on reflective writing ensured that students understood how to engage in meaningful reflection and capitalise on its benefits for their learning journey.

On the other hand, students who did not receive the intervention (IT-02 and IT-05) did not follow the abovementioned procedure. Students from IT-02 received weekly reflection questions that were not a part of any intervention. Reflection questions in IT-02 were about thoughts and feelings for the exercises performed every week, e.g., "Where did you encounter struggles this week, and what did you do to deal with them?". Students in IT-05 did not have any reflection questions designed for the students. Students' written reflections were downloaded from Canvas LMS biweekly, and only the data of the students who consented to participate in both pre and post-MAI surveys were further analysed. These written reflection data were used to address RQ1 and RQ3.

3.5 Data Analysis

A range of data analysis methods were incorporated in this research to answer the research questions, including both quantitative and qualitative data analysis. Table 6 provides a comprehensive summary of the analysis methods employed with the data collected during the Spring and Autumn 2023 sessions, aligning with the research questions addressed in this study. To address RQ1.1., epistemic network analysis (ENA) was utilised and for RQ1.2. and RQ2.1, a combination of PowerBI for visualisation and statistical analysis methods using SPSS, was implemented. RQ2.2. was addressed by implementing the process mining technique using Disco. To address the last research question (RQ3), linguistic inquiry word count (LIWC) was used. The following sub-sections represent a comprehensive view of the methods implemented for Epistemic Network Analysis, Process Mining, and Linguistic Inquiry Word Count.

Table 6: Overview of the Research Methodology

Research question	Analysis Method	Data Utilised
RQ1: What are the differences between IT students with high and low final scores in terms of their metacognition?		
RQ1.1. How are metacognitive processes distributed in the written reflections of IT students with high and low final scores?	Epistemic Network Analysis	RQ1.1.: High and low-score students' written reflections and final scores RQ1.2: Pre and Post-MAI scores and final scores of high and low-score students $N_{IT-01} = 14$ $N_{IT-02} = 8$ $N_{IT-04} = 19$
RQ1.2. What is the difference between high and low-score IT students' metacognitive awareness?	Visual (PowerBI) and Statistical Analysis (SPSS)	
RQ2: How do semester-long metacognitive interventions have an impact on IT students' metacognition?		
RQ2.1. How do IT students' pre- and post-metacognitive scores differ between students who have experienced metacognitive interventions and those who have not?	Visual (PowerBI) and Statistical Analysis (SPSS)	RQ2.1.: Pre and Post-MAI of all students who consented to participate RQ2.2.: LMS activity logs of all students who consented to participate $N_{IT-04} = 40$ $N_{IT-05} = 16$
RQ2.2. Are there any differences in the temporal patterns in IT students' learning traces between students who have experienced metacognitive interventions and those who have not?	Process Mining	
RQ3. Which linguistic features in IT students' written reflections are significantly associated with their self-reported metacognitive awareness and academic scores?	Linguistic Inquiry and Word Count	RQ3: Pre and Post-MAI scores, students' final scores, and written reflections of all students who consented to participate $N_{IT-04} = 40$

3.5.1 Data Preparation for RQ1

Before proceeding with understanding the data preparation process for the ENA model, it is essential to comprehend the overview of data collection and the research question they aimed to answer (see Figure 8). To address RQ1 (*What are the differences between IT students with high and low final scores in terms of their metacognition?*), ENA was utilised. Figure 8 illustrates an overview of the process of addressing RQ1, including the data being analysed. RQ1, which was further subdivided into RQ1.1 (How are metacognitive processes distributed in the written reflections of IT students with high and low final scores?) and RQ1.2 (What is the difference between high and low-score IT students' metacognitive awareness?). After collecting the data from both the Autumn and Spring 2023 sessions, data was processed for analysis. Only students who participated in both pre-MAI and post-MAI surveys were included for further processing; this ensured that students who had complete engagement with the surveys were included. Additionally, for RQ1, only post-MAI data was taken into consideration to maintain the consistency of the timeline with the final score.

To ensure the quality of the data, this preprocessing procedure comprised checking duplicates and missing values using Python and cleaning the reflection text data to remove any unnecessary characters using Python and Excel. The pre-processed data was subdivided to explore RQ1.1 and RQ1.2. A quartile check method was implemented to filter the data into high and low-score students. The final scores of students that fell under the upper quartile were considered "high-score", and final scores that fell under the lower quartile were considered "low-score" students. After processing the data, IT-01 had 14 students ($N_{\text{High-score}} = 7$ and $N_{\text{Low-score}} = 7$; $N_{\text{Reflections}} = 68$), IT-02 had 8 students ($N_{\text{High-score}} = 6$ and $N_{\text{Low-score}} = 2$; $N_{\text{Reflections}} = 85$), IT-04 had 19 students ($N_{\text{High-score}} = 10$ and $N_{\text{Low-score}} = 9$; $N_{\text{Reflections}} = 130$), and IT-05 had no reflections, thus, was excluded from this analysis. While RQ1.1 was addressed using the ENA model (a comprehensive discussion of this process is discussed below), RQ1.2. was analysed using exploratory and statistical analysis using PowerBI and SPSS. Due to a small sample size, a Mann-Whitney (non-parametric) test was used to compare differences between high and low-score students (Gibbons & Chakraborti, 2014). The following sub-section demonstrates the framework implemented for epistemic network analysis, including the steps involved in the process.

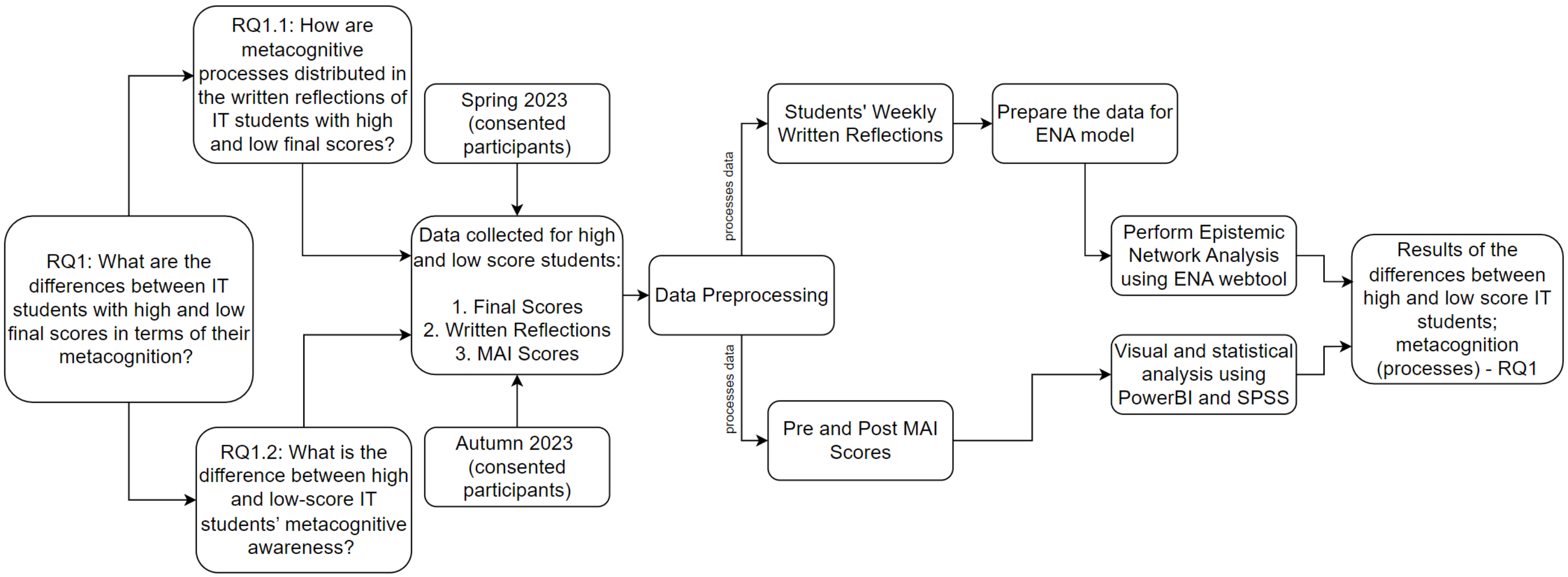


Figure 8: Overview of the Process of Addressing RQ1

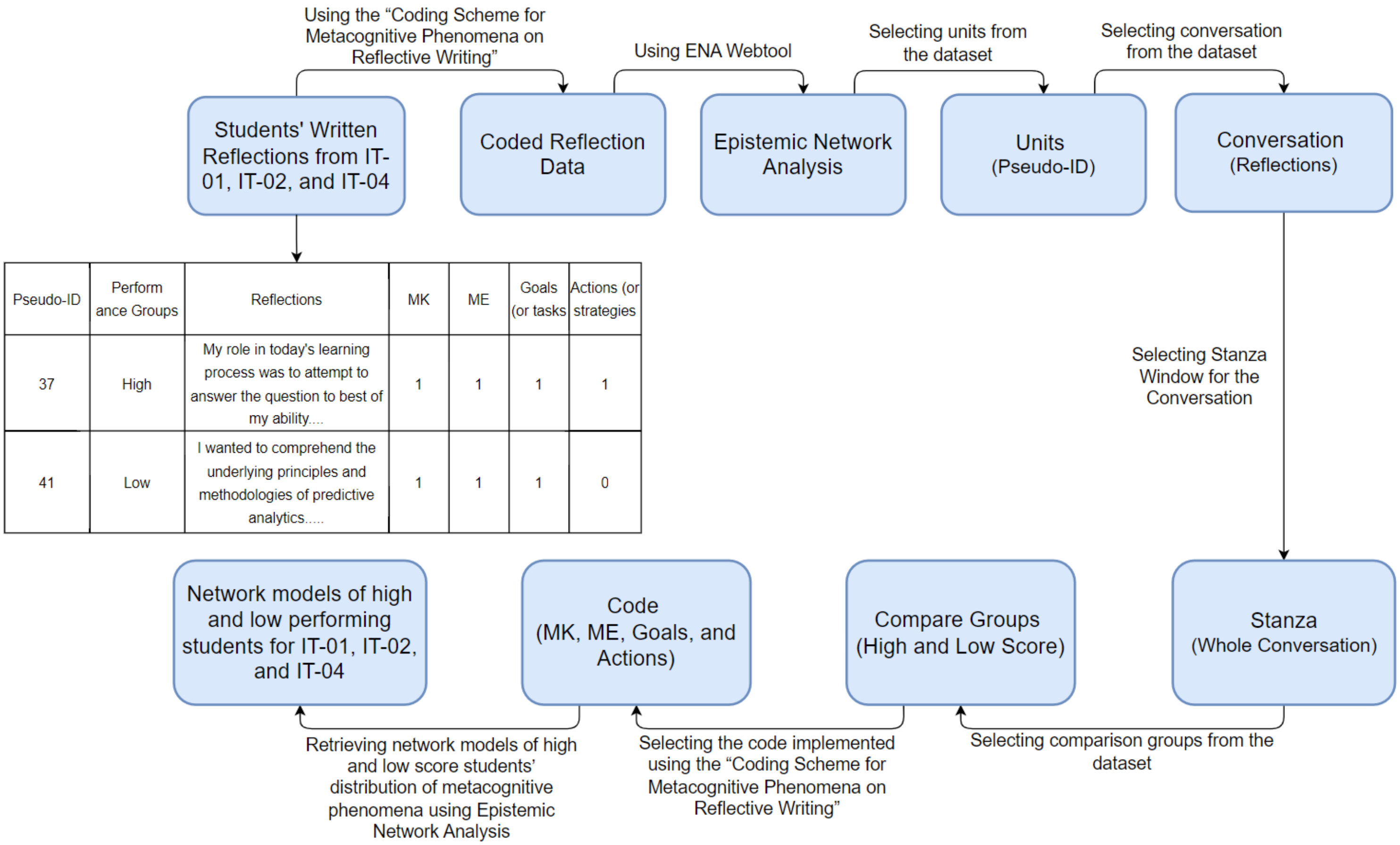
3.5.2 Epistemic Network Analysis (ENA)

Epistemic Network Analysis (ENA) is a novel method that identifies connections between cognitive components through the quantification, visualisation, and interpretation of network data. Before proceeding with preparing the data for analysis using ENA, it is essential to understand the necessary preliminary steps. As discussed earlier (see section 2.4.1), the theoretical foundation for ENA lies in the Epistemic Frame Theory (Shaffer & Ruis, 2017). According to this theoretical framework, learning involves more than simply acquiring information or skills; it consists of transforming the epistemic network of an individual - a complex relationship tying together knowledge, beliefs, and abilities (Csanadi et al., 2018) (see section 2.4.1 for a detailed concept and justification for using the ENA). As ENA produces the interconnected elements' patterns of connections with summary statistics, using this method allowed us to visualise the existing nuanced interactions among the metacognitive phenomena within the epistemic network. This model segments data for analysis and models the relationships between objects. ENA web tool[5] was used to perform the Epistemic Network Analysis. To perform visualisations using the ENA web tool, a few steps are needed to set up the model. The following sub-section walks through the steps that were performed to set up the model with a comprehensive framework. Modelling of these networks in the ENA web tool is also available in the Appendix F.

3.5.2.1 Overview of Step-by-Step ENA Network Modelling

Figure 9 represents an overview of the framework implemented for modelling the networks of high and low-score students using Epistemic Network Analysis. Using the "Coding Scheme for Metacognitive Phenomena on Reflective Writing" from Table 7, the reflection data was coded in the first step for IT-01, IT-02, and IT-04. The coded reflections were uploaded to the ENA web tool for performing the epistemic network analysis. Using the ENA web tool, the following process included selecting the units, conversations, and stanza window, as well as comparing groups and data codes. The resulting visualisations are the network graphs of high and low-score students from IT-01, IT-02, and IT-04, implementing epistemic network analysis and illustrating the distribution of the metacognitive phenomena. The detailed process followed for each step is described in the following points.

[5] Epistemic Network Analysis Webtool is a platform for performing epistemic network analysis.



Pseudo-ID	Performance Groups	Reflections	MK	ME	Goals (or tasks	Actions (or strategies
37	High	My role in today's learning process was to attempt to answer the question to best of my ability....	1	1	1	1
41	Low	I wanted to comprehend the underlying principles and methodologies of predictive analytics.....	1	1	1	0

Figure 9: Overview Step-by-Step ENA Modelling

(1) **Units (Step 1):** Units can be individuals, groups, or concepts. For the dataset in this research, pseudo-IDs were considered as units.

(2) **Conversations (Step 2):** Conversations are the qualitative dialogue data implemented to illustrate the network graphs. The weekly reflections from the dataset served as the conversation for the ENA model.

(3) **Codes (Step 3):** Inspired by the work of Wu et al. (2020) and following Flavell's (1979) metacognitive components, the reflections were coded. To keep consistency, we followed the exact terminology of the metacognitive components used in Flavell's (1979) work, i.e., metacognitive knowledge, metacognitive experiences, goals (or tasks), actions (or strategies) (see section 2.1). Table 7 outlines the coding scheme that was followed for performing ENA. A comprehensive process was followed to calculate the inter-rater reliability. Three researchers (primary researcher and supervisory panel) discussed and carefully outlined the coding scheme (presented in Table 7) required to analyse the distribution of metacognitive phenomena in high and low-score students' written reflections. The primary researcher (R1) coded the entire reflection data based on the discussed framework. After that, rater 2 (primary supervisor from the panel) coded 30% of the reflections using the coding scheme for metacognitive phenomena on reflective writing (Table 7). As there were two rates, a Cohen's Kappa inter-rater reliability test was performed for the coded reflections between the two coders, which resulted in a value of 88.85% agreement.

Table 7. Coding Scheme for Metacognitive Phenomena on Reflective Writing

Code	**Metacognitive Phenomena**	**Aligned Sub-component**	**Description**	**Examples from Written Reflections**
MK	Metacognitive Knowledge	Person, Task, and Strategy	Individuals' understanding of their own cognitive processes comprises knowledge about beliefs and abilities, cognitive strategies, and situations in which these strategies can be applied (Flavell, 1987).	"Firstly, I realised that data cleaning and preprocessing are critical steps in the entire analysis process. I learned how to identify and handle missing or aberrant values more efficiently. Secondly, I learned how to utilise various libraries in Python, like Pandas, to better comprehend data and create visual representations. I also realised that there are many skills I still need to learn and master to

Code	Metacognitive Phenomena	Aligned Sub-component	Description	Examples from Written Reflections
				perform data analysis more effectively.”
ME	Metacognitive Experiences	Feeling of Knowing, Judgement of Learning	Metacognitive experiences refer to individual’s internal responses to their own cognitive process, including feelings of knowing or not knowing and judgement of learning.	“When I was reading about the retail sector, it was fun; however, when I started reading about the automobile industry and government applications, it was a task I didn't enjoy.”
Goals (or Tasks)	Goals (or Tasks)	Setting Goals, Goal Adjustments, Strategic Planning	As defined by (J. H. Flavell, 1979), goals (or tasks) refer to the desired outcome of a cognitive process. Further elaborated in (Flavell, 1987) work, it involves setting goals, adjusting goals, and engaging in strategic planning to achieve a goal.	“My goals while learning and completing the activities related to predictive analytics were to understand IBM Watson's capabilities and determine how to understand its solutions more effectively…... Halfway through the exercise, I think our goal changed from completing it to playing around with the tool, giving it different samples and analysing the outputs.”
Actions (or Strategies)	Actions (or Strategies)	Monitoring Strategies, Adapting Strategies, Evaluating Performance	Actions (or strategies) are cognitive behaviours implemented to achieve a goal. (Flavell, 1987) further elaborated this, emphasising monitoring, adaptation strategies, and evaluating these cognitive behaviours to accomplish a goal.	“While working on this week's tutorial questions related to prescription analytics, resources like internet blog posts, articles, and journal papers are being used...... I think internet blog posts are the most important resource that I have used.”

(4) **Comparison Groups (Step 4):** Comparison groups refer to two or more groups within a dataset that can be compared based on the conversation's data. RQ1 aimed to understand the metacognitive phenomena difference between high and low-score students. Therefore, the comparison groups for this study were high-score and low-score learners from IT-01, IT-02, IT-04, and IT-05.

(5) **Stanza Window (Step 5):** As discussed earlier, the stanza method is utilised to segment the data for analysis. The stanza window of "whole conversation" was chosen in this data preparation process. Analysing the cooccurrences within this window allowed us to evaluate how each reflection demonstrates metacognitive phenomena.

3.5.3 Data Preparation for RQ2

Figure 10 portrays an overview of the process of addressing RQ2, which includes process mining. RQ2 was subdivided into RQ2.1 (How do IT students' pre and post-MAI scores differ between students who have experienced metacognitive interventions) and RQ2.2 (Are there any differences in the temporal patterns in IT students' learning traces between students who have experienced metacognitive interventions and those who have not?). As discussed in the section 3.4, only the Spring 2023 semesters' data (IT-04 and IT-05) was utilised to address RQ2. Students who received the metacognitive intervention (IT-04) followed sequences of activities (see section 3.4.4) during the weekly tutorials. On the contrary, students who did not receive the intervention only participated in the weekly collaborative tasks. Students who participated in both of the surveys were only considered for further processing (as both pre and post-MAI scores are required to analyse the differences). Missing and duplicate records were checked using both Python and Excel. After processing, IT-04 had 40 students with 12077 event logs from Canvas LMS, and IT-05 had 16 students with 8424 event logs. While learners from IT-4 received metacognitive interventions, the IT-05 cohort did not receive any interventions. The processed data was further analysed to address RQ2.1. PowerBI was used to perform exploratory analysis, and SPSS was used to examine the significance. A Mann-Whitney (non-parametric) test was used to compare differences as the sample size was small (Gibbons & Chakraborti, 2014). For RQ2.2, on the other hand, several steps of the data process were followed before importing the data into the Disco platform. The bi-weekly Canvas event logs were integrated into one Excel file at first, then proceeded with checking duplicates and missing values in the record. The following steps involved incorporating the analytical framework (discussed in the following section in Figure 11), which included identifying the learning actions and sub-actions, followed by low-level mapping and high-level coding of regulation of cognition. However, two types of contents were excluded from further analysis: (1) Course people view, as it did not demonstrate any metacognitive components, and (2) unidentifiable/ banner images, e.g., canvas banner, image.png, image-1.png.

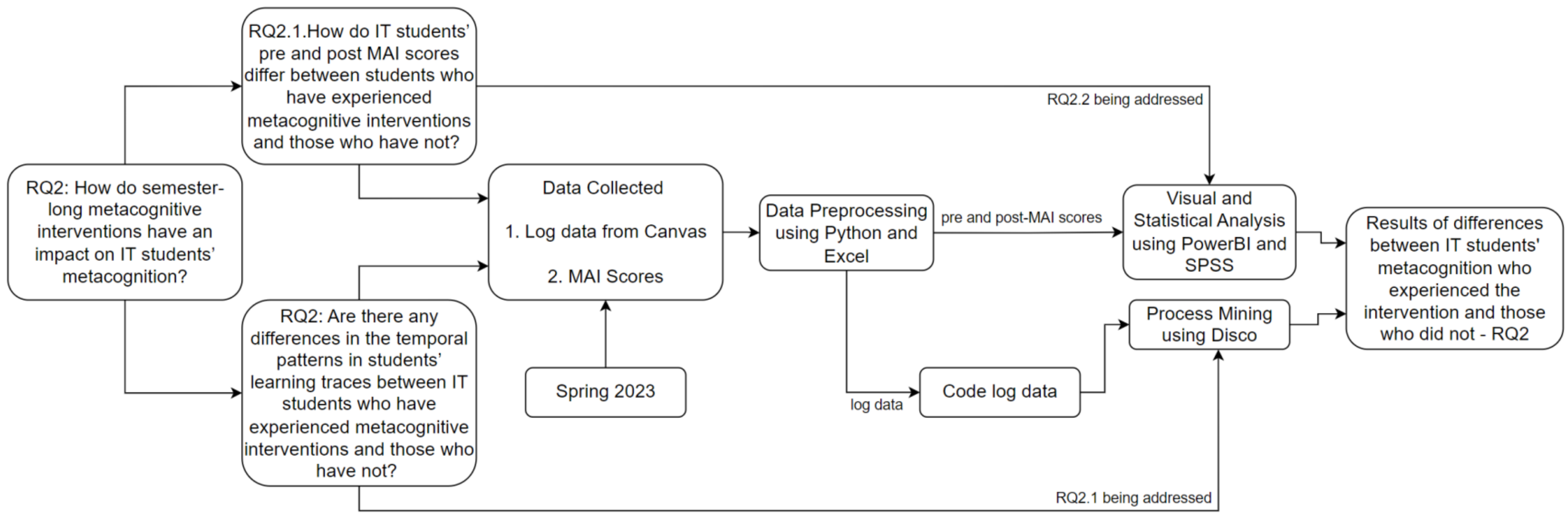


Figure 10: An Overview of the Process of Addressing RQ2 and PM

3.5.4 Process Mining (PM)

In this research, process mining (PM) was implemented to analyse the temporal patterns of students and understand the differences between the cohort who received metacognitive interventions and those who did not, addressing RQ2.2. As mentioned in the section 2.4.2, process mining involves extracting event logs from learning management systems to visualise and analyse processes within. This study utilises the Disco Miner, an advanced process discovery model based on the Fuzzy Miner framework, to explore temporal patterns within the extracted event logs (see section 2.4.2 to understand the rationales behind choosing this analysis). With its enhanced capabilities for process analysis and visualisation, Disco Miner proves invaluable for understanding complex processes and uncovering nuanced temporal relationships (Günther & Rozinat, 2012). Steps followed to perform in the Disco software are available in Appendix G. Tailored to this study's research, an overview of the analytical framework is illustrated in Figure 11, which was designed and inspired by the analytical framework of Saint et al. (2021) for self-regulated learning implementing process mining. The following sub-section discusses the analytical framework and coding scheme for performing PM.

3.5.4.1 Analytical Framework and Coding Scheme for PM

The primary component in this process is the learning management system; for this study, it was Canvas LMS. Students interact with the learning components using the learning management system (LMS). Canvas LMS captures students' traces, which were utilised as event logs for process mining. Figure 11 highlights the analytical framework for performing process mining, including the process followed to prepare and code the raw data. Table 8 represents the "Action Library", which was retrieved from the raw Canvas event logs (see Figure 11 to understand the role of this table in the analytical framework). Table 9 represents the "Hierarchical Library", which was created using the actions from the "Action Library" (see Figure 11 to understand the role of this table in the analytical framework). The process of creating this action and hierarchical library is illustrated in Figure 11, and the steps of this process are discussed below. A few steps were performed to develop a coding scheme for analysis.

The first step was extracting the learning "actions" and learning "sub-actions" from the "content type" data of the canvas raw event logs (Figure 11), which are column 1 and column 2 of Table 8. This process was performed by extracting the *middle portion* of the "content type" from canvas raw event logs, as it represents the type of "learning action" taken (see Figure 11). For example, for the first record in Figure 11, "course.quizzes.quiz" content type, the primary learning "action" was "quizzes". Another example is for the "course.pages.page" content type; the primary learning "action" was "pages". Thus, for those two records, the learning "actions" were "Quizzes" and "Pages" (column 1 of Table 8).

The second step was extracting the learning "sub-actions". The learning "sub-actions" were coded by looking at the content name, content type, times viewed, and times participated (see Figure 11). There were mainly two types of sub-actions: (sub-actions)_View and (sub-actions)_Participation. If the times participated was "0" and the times viewed was "more than 0", it was coded as (sub-actions)_view. Alternatively, if the times participated was "more than 0", it was coded as (sub-actions)_Participation (see Figure 11). For example, from Figure 11, "Week 9 Lecture Notes" content was coded as "Lecture_Note_View" in the learning "sub-action" as times participated was 0 and times viewed was 2. Alternatively, as the "Week 9 Quiz" content type had the participation of "more than 0", it was coded as "Quiz_Participation" (see Figure 11). It is important to note that reflection tasks were set as a quiz in IT-04. Thus, it is reflected as a quiz in the content type. For example, the third record ("Week 9 Reflection") in Figure 11 was coded as Reflection_Participation as the content was weekly reflection and participation was "more than 0". These extracted learning "sub-actions" are reflected in Table 8, with their descriptions.

In the third step, a low-level mapping was created, inspired by Cerezo et al. (2020)'s low-level mapping of Moodle event logs (see Figure 11). Table 9 outlines a comprehensive view of the low-level mapping performed using the "Action Library" from Table 8. The low-level mapping was performed following the data from the learning "sub-actions" and the "content name" from the raw event logs data (see Figure 11). For example, for the first record in Figure 11, the learning sub-action was "Quiz_Participation", and the content name was "Week 9 Quiz", which represents the weekly quizzes. Thus, for this record, it was mapped as "Weekly Quiz Participation" in the "low-level mapping" in column 2 of Table 9.

In the fourth step, a "high-level coding" for the regulation of the cognition aspect of metacognition was performed on the event logs (see Figure 11 and Table 9). Students' traces from Canvas LMS were coded following Schraw and Dennison's (1994) "Regulation of Cognition" (i.e., planning, information management, monitoring, debugging, and evaluation) metacognitive component (see section 3.4.1). However, debugging was excluded from the coding scheme as it refers to the strategies implemented to correct understanding and errors in performance, which were not retrievable from the Canvas event logs. As defined by Schraw and Dennison (1994), metacognition is one's ability to understand and control one's own learning, and regulation of cognition facilitates those control aspects; aligning with these definitions, few logs/actions were coded as "Completing a task", as they did not fall under any regulative aspects of metacognition. Such actions included submitting a weekly assignment that was a compulsory task for learners to complete. However, this action does not reflect any regulative elements of metacognition, as it was a mandatory task for learners to complete and did not involve conscious control of their learning. While writing reflections was also a graded task of the weekly learning component, this action was coded as "evaluation" since students are prompted to reflect on their learning. For example, in the first record in Figure 11, the "high-level coding" was mapped as "Completing a task", as quiz participation was a mandatory task for learners to complete and did not involve conscious control of their learning. Similarly, the "Weekly Progress Check View" in Figure 9 was coded as "Monitoring" as students viewed their grades to monitor their current performance in the subject. This high-level mapping is comprehensively outlined in Table 9.

In the final step, the coded high-level and low-level mapping, including the timestamp value, was utilised to create the process models of students who experienced the intervention (IT-04) and those who did not (IT-05), using Disco. These process models represent the temporal patterns of the students for the whole semester. It is important to note that, to create the process models, both low-level mapping and high-level coding were considered for activities for comprehensive and granular analysis. Additionally, to avoid spaghetti-like process models, a filter of 41.8% "activities" was chosen in the software for both process modes (IT-04 and IT-05) to keep consistency. Appendix G contains detailed steps followed for performing process mining in Disco software.

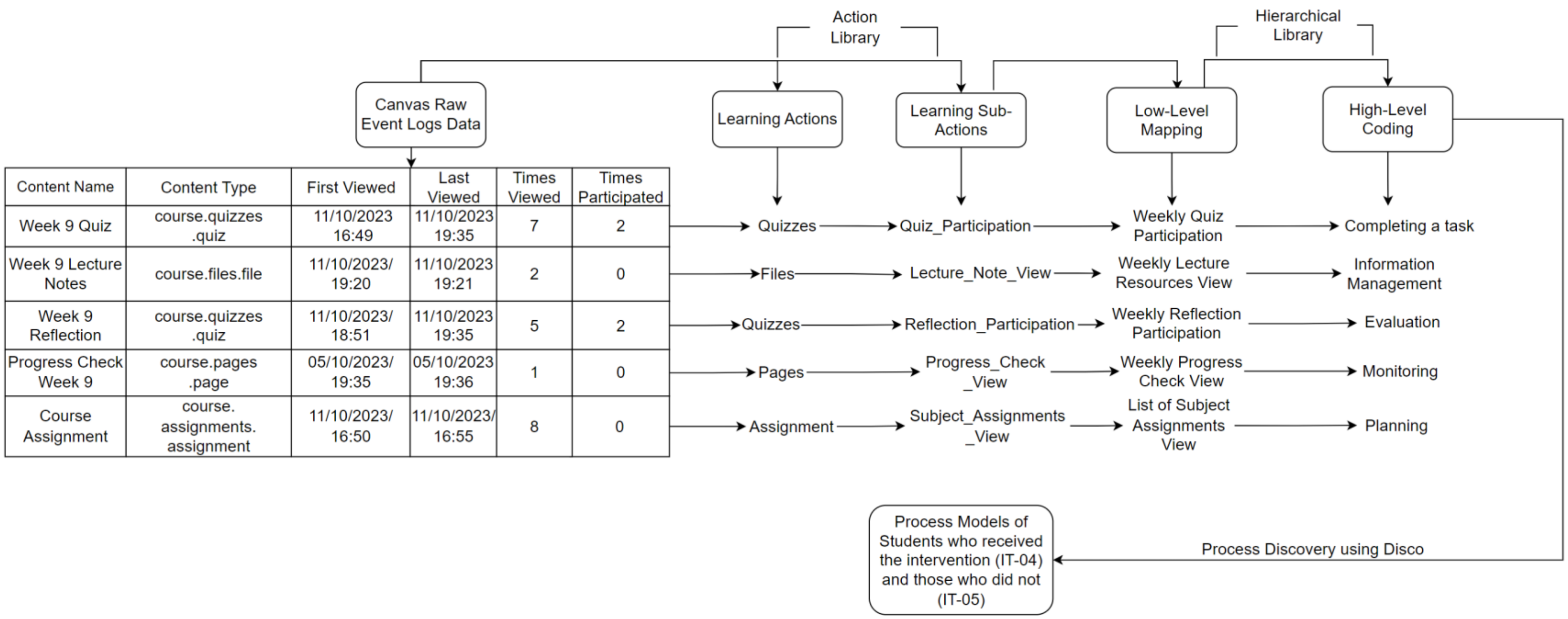


Figure 11: Analytic Framework Implemented for Process Mining

Table 8: "Action Library" for Coding the Data for Process Mining

Actions	Sub-actions	Descriptions
Assignment	Assignments_View	Learners view the assignments submission page.
	Assignment_Participation	Learners participate in submitting course assignments.
	Reflection_View	Learners View Weekly Reflections
	Tutorial_View	Learners open the weekly tutorial submission page.
	Tutorial_Participation	Learners participate in submitting weekly tutorials.
	Assignment_Guideline_View	Learners view assignment guidelines.
	Plagiarism_Quiz_View	Learners view plagiarism quizzes to test knowledge on plagiarism.
	Assignments_List_View	Learners view lists of assignments.
Quizzes	Quiz_Participation	Learners participate in submitting weekly quizzes
	Quiz_View	Learners view weekly quizzes.
	Plagiarism_Quiz_View	Learners view the plagiarism quiz to test their knowledge of plagiarism.
	Plagiarism_Quiz_Participation	Learners participate in submitting a plagiarism quiz to test their knowledge of plagiarism.
	Reflection_View	Learners view weekly reflections set up as quizzes.
	Reflection_Participation	Learners participate in submitting weekly reflections set up as quizzes.
	Quiz_List_View	Learners view the subject quiz list.
	Knowledge_Test_View	Learners view prior knowledge tests.
	Knowledge_Test_Participation	Learners participate in submitting the prior knowledge test.
Pages	Tutorial_Content_View	Learners view weekly tutorial content page
	Progress_Check_View	Learners view weekly progress checks.
	Prepare_Resource_View	Learners view the weekly prepare resources page.
	Weekly_Content_Overview_View	Learners view the weekly content overview page.
	Drop-In Sessions View	Learners view the drop-in sessions information page.
	Library_Guidelines_View	Learners view the UTS Library usage guidelines page.
	Plagiarism_Resources_View	Learners view resource pages on plagiarism.
	Subject_Resource_View	Learners view pages on subject resources.
	Getting_Started_Guidelines_View	Learners view getting started on the subject page.
	GenAI_Guide_View	Learners view the page on guidelines on using Generative AI in this subject.

Actions	**Sub-actions**	**Descriptions**
	Support_Resource_View	Learners view help and support on the information page dedicated to academic and student support.
Discussion	Weekly_Update_Announcement_View	Learners view announcements on weekly updates.
	Group_Presentation_Peer_Feedback_View	Learners view their peers' reviewed feedback for group presentations.
	Group_Presentation_Peer_Feedback_Participation	Learners participate in providing peer review feedback on group presentations.
	Discussion_Forum_View	Learners view the discussion forum on general Q/A on the subject.
	Greetings_Page_View	Learners view the greetings page to get to know each other.
	Greetings_Page_Participation	Learners participate in greeting early in the semester.
	Group_Formation_View	Learners view group formation details.
	Group_Formation	Learners form a group for subject assignments and weekly tutorials.
	Announcement_View	To view announcements related to (1) student feedback survey (evaluation), (2) feedback for the weekly in-class reflections, and (3) updates on upcoming changes and notices affecting the subject's timeline
	Presentation_Order_View	Learners view group presentation order.
	Metacognitive_Survey	Learners view/participate in metacognitive surveys.
Files	Lecture_Note_View	Learners view files on weekly lecture notes
	Plagiarism_Resource_View	Learners view files related to plagiarism resource files.
	Attachment_View	Learners view attachments (figures, additional CSV and Excel files)
Grades	Grades_View	Learners view their subject grades.
External Tools	Subject_Outline_View	Learners view the subject outline stored on another system at the institution.

Table 9 below representing the "Hierarchical Library" that was created using the actions from the "Action Library".

Table 9: "Hierarchical Library" for Coding the Data for Process Mining

High-Level Coding	Description	Low-Level Mapping
Planning	To view weekly updates on announcements (e.g., week 9 update, week 8 update and public holiday)	**Weekly Update Announcement** Weekly_Update_Announcement_View
	To view the list of quizzes in the course	**List of Subject Quiz View** Quiz_View
	To view the list of course assignments	**List of Subject Assignments View** Assignments_List_View
	To view the weekly prepare resources (e.g., week 6 prepare)	**Weekly Prepare Resources** Prepare_Resource_View
	To view the overview of the weekly content (e.g., week 8 overview)	**Weekly Content Overview View** Weekly_Content_Overview_View
	To view the guidelines for using the UTS library	**UTS Library Guideline View** Library_Guidelines_View
	To view assignment guidelines	**Assignments Guidelines View** Assignment_Guideline_View
	To view the subject outline	**Subject Outline View** Subject_Outline_View
	To view the getting started guideline delivered at the beginning of the semester	**Getting Started Guideline View** Getting_Started_Guidelines_View
	To view the greetings discussion forum as an introductory platform at the beginning of the semester	**Discussion Forum Greetings Page View** Greeting_Page_View
	To form a group for subject assignments and weekly tasks	**Discussion Forum Group Formation** Group_Formation
	Viewing the presentation order for group participation	**Group Presentation – Viewing Presentation Order** Presentation_Order_View
	To participate in the greetings discussion forum as an introductory platform at the beginning of the semester	**Discussion Forum Greetings Page Participation** Greetings_Page_Participation
	To view announcements related to the upcoming events, group formations, and deadlines	**Subject Announcement View** Subject_Announcement_View
Information Management	To view the weekly tutorial content that comprises tutorial questions, links to resources, and allocated time for each task)	**Weekly Tutorial Content View** Tutorial_Content_View

High-Level Coding	Description	Low-Level Mapping
	(e.g., Engage-Week 8 Lecture Notes and Tutorial Questions)	
	To view the study and personal help and support page	**Help and Support Resource View** Support_Resource_View
	To view the files attached with the learning content	**Attachment View** Attachment_View
	To view course assignments containing details on guidelines, instructions, task details, FAQs, and assessed rubrics.	**Subject Assignments View** Assignments_View
	To view the details of the weekly classes, including time, venue, and online drop-in session details.	**Weekly Classes and Drop-In Session Details** Drop-In_Sessions_View
	To view the weekly tutorial submission page	**Weekly Tutorial Submission View** Tutorial_View
	To view the subject's discussion forum	**Discussion Forum View** Discussion_Forum_View
	To view the resources on weekly lectures	**Weekly Lecture Resources View** Lecture_Note_View
	To view the support resources, including personal and academic support	**Subject Resources View** Support_Resource_View
	To view the resources on avoiding plagiarism	**Avoiding Plagiarism Resources View** Plagiarism_Resource_View
	To view the faculty guidelines on Generative AI, containing details on how Generative AI should be incorporated.	**GenAI Guide View** GenAI_Guide_View
Monitoring	To view the weekly progress	**Weekly Progress Check View** Progress_Check_View
	To participate in the prior knowledge test	**Prior Knowledge Test Participation** Knowledge_Test_Participation
	To view the prior knowledge test content	**Prior Knowledge Test View** Knowledge_Test_View
	To view the plagiarism quiz	**Avoiding Plagiarism Quiz View** Plagiarism_Quiz_View
	To participate in the quiz on avoiding plagiarism	**Avoiding Plagiarism Quiz Participation** Plagiarism_Quiz_Participation

High-Level Coding	Description	Low-Level Mapping
	To view the subject announcements.	**Subject Announcement View** Announcement_View
Evaluation	To participate in the weekly reflections to reflect on the learning process and strategies implemented while performing a task	**Weekly Reflection Participation** Reflection_Participation
	To view subject grades	**Subject Grade View** Grades_View
	To view the weekly reflection page for participation	**Weekly Reflection View** Reflection_View
	To participate in providing peer feedback during the group presentation	**Group Presentation - Peer Feedback Participation** Group_Presentation_Peer_Feedback_Participation
	To view the discussion forum on peers' feedback during the group presentation	**Group Presentation - Peer Feedback View** Group_Presentation_Peer_Feedback_View
	To view or participate in the metacognition survey	**Metacognition Survey** Metacognition_Survey
	To view the subject announcements related to the student feedback survey	**Subject Announcement View** Announcement_View
Completing a task	To participate in the weekly quizzes	**Weekly Quiz Participation** Quiz_Participation
	To participate in the weekly tutorial submissions	**Weekly Tutorial Submission Participation** Tutorial_Participation
	To participate in the subject assignments	**Subject Assignments Participation** Assignment_Participation

3.5.5 Data Preparation for RQ3

Research question 3 aimed to identify the significant linguistic features from students' written reflections that were associated with self-reported metacognitive awareness and final score. The reflection writing activity was one of the components of weekly tutorials (refer to section 3.4.4 for details). For granular analysis, the Post-MAI score and the subject's final scores were divided into quartiles using the Pandas library and the quantile method in Python. This approach allowed us to identify the patterns and differences among students within each quartile (Q), illustrating a more nuanced understanding of the relationship between metacognitive awareness and academic performance. Only students who consented to participate and who responded to both pre-MAI and post-MAI surveys were considered for further analysis that ensured consistent engagement with the survey. For both MAI and final score quartiles, they are represented – Quartile one as Q1, Quartile two as Q2, Quartile three as Q3, and Upper quartile as UQ.

For Q1, the MAI score is less than 194.75, and the Final score is less than 74.80. This suggests lower levels of metacognitive awareness and academic performance. Q2's MAI score ranges from 194.76 to 205, and the Final score ranges from 74.80 to 80, indicating a moderate level of metacognitive awareness and academic performance compared to Q1. For Q3, the MAI score is up to 209.50, and the final score is up to 86.65, suggesting better metacognitive awareness and academic performance compared to Q2, indicating a higher level of proficiencies. Lastly, Upper Quartile (UQ) MAI scores are above 209.50, and final scores are above 86.65. Students from this quartile demonstrate the highest levels of metacognitive awareness and academic performance among all the other quartiles/ groups. The processing of reflection data followed a few steps – (1) null values were checked and deleted by implementing the isnull() method in Python, (2) duplicated records were checked utilising Excel's data duplicate check function, and (3) any unnecessary characters except emoticons, were removed from the reflection data (LIWC can analyse emoticons). After preprocessing the data, $N_{reflections} = 362$ and $N_{students} = 40$. However, for answering RQ3, only post-MAI data was considered to represent the metacognitive awareness to align with the timeframe of the collected final score; this decision was critically analysed and allowed consistency in the collected scores' timeframe.

3.5.6 Linguistic Inquiry Word Count

Linguistic Inquiry Word Count or LIWC was utilised in this study to understand the significant linguistic features in learners' written reflections that are associated with their metacognitive awareness and final score, addressing RQ3 (see section 2.4.3 to understand the motivations for choosing this method). Figure 12 illustrates an overview of the flow of addressing RQ3. LIWC offers efficient and insightful text analysis into psychological states, and its validity has been tested and confirmed in diverse contexts (Boyd et al., 2022). In developing the LIWC 2022 dictionary, several steps of the process were followed – (1) word collection, (2) judge rating phase, (3) base rate analyses, (4) candidate word list generation, (5) psychometric evaluation, (6) refinement phase, and (7) addition of summary variables (Boyd et al., 2022). LIWC analyses the text input and categorises them into various linguistic and psychological dimensions, operating on predefined words from the dictionary. Of all the linguistic features LIWC is capable of detecting, only a few were carefully assessed and selected as a part of this study, aligning with the research question (refer to section 1.2 for research questions and Table 10 for the selected LIWC features). IT-01 and IT-03 were excluded from this analysis as there was insufficient reflection data to analyse significant linguistic features. Similarly, data from IT-05 was not included as there was no response in reflection from learners. Several features were selected from the LIWC software to address the research question (see section 1.2).

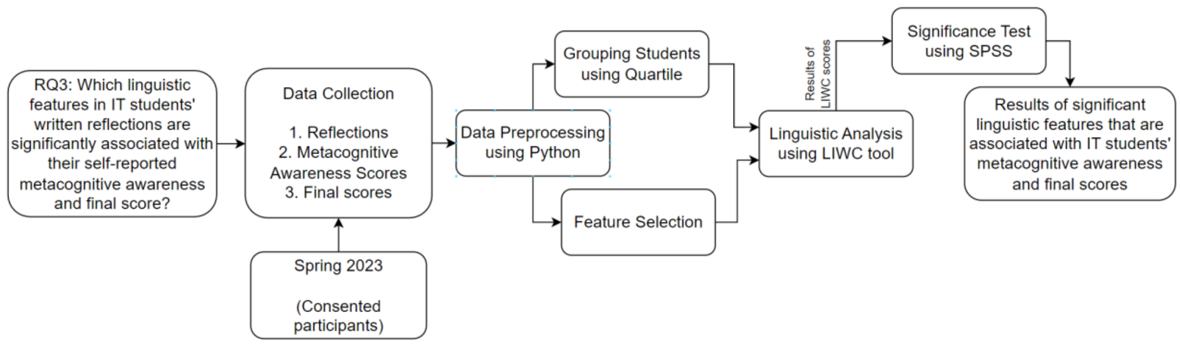


Figure 12: An Overview of Addressing RQ3

The following steps are performed for LIWC analysis in this study – (1) Data preparation, (2) Select dictionary from the LIWC software, (3) Select categories on which LIWC will perform the analysis, and (4) Analysing the results. Data preparation included the written reflections, which were to be formatted properly for LIWC analysis. This included cleaning the data by changing all text cases to lowercase and by removing any irrelevant content, such as headings and special characters, from the reflections and ensuring that the text is in a format that LIWC can process. Next, the relevant dictionary from the LIWC software is chosen, which is the LIWC-22 Dictionary (English) in this case. Then, the related metacognitive components of Flavell's (1979) framework, i.e., Metacognitive Knowledge (MK), Metacognitive Experiences (ME), Goals (or tasks), and Actions (or strategies), were mapped to the relevant LIWC categories either based on the existing literature or that reflect the metacognitive components' descriptions. The key to mapping LIWC categories to metacognitive components lies in interpreting the relevance of each category to aspects of metacognition. For example, categories like "Cognitive Process", "Insights", and "Causation" (in column 1 of Table 10) are directly related to metacognitive strategies and reflections about learning and "Tentative" help identify the students' confidence in their knowledge and strategies. Linguistic Dimensions - "Personal Pronouns" indicate self-regulation and self-awareness levels.

Table 10 represents the concept map outlining the selection of features from the LIWC categories and their relationship to Flavell's metacognitive components. For example, ME → Tone → the feelings and judgements that arise during learning and can influence how students approach the task. These experiences could include realising a task is more difficult than expected or feeling confident about one's understanding. After this, the written reflections were uploaded to the LIWC software. LIWC then processed these texts by (a) word count, where LIWC examines each word in the text and compares it against its internal dictionaries, which categorises words into various linguistic, psychological, and emotional dimensions, and (b) category matching, where each word that matches a category in the LIWC dictionary is counted toward that category. For example, words like "good", "happy", and "nervous" were counted under the "Affect" category. After processing, LIWC provided the output that showed the percentage of words in each category relative to the total number of words in the written reflection. A Kruskal-Wallis test was performed at the end to evaluate significance, as it is a non-parametric test that does not require the assumption of normal distribution and is implemented for comparing significances between more than two groups. The details of these steps, as screenshots, are also available in Appendix H.

Table 10: LIWC Features and Their Relationship to Metacognition

LIWC Category	**Abbreviations**	**Frequently Used Exemplars**	**Relationship to Metacognition**	**Metacognitive Component**
Analytical Thinking	Analytic	Metric of logical and formal thinking	Higher analytical thinking suggests proficient reasoning skills, logical thought processes and hierarchical thinking (Simonovic et al., 2023). Analytical thinking can be advantageous for metacognitive reflections since it facilitates the understanding and organisation of ideas.	MK and ME
Tone	Tone	Degree of positive or negative tone	Sentiment in reflective writing. Gibson et al. (2016) highlighted that positive and negative tones affect metacognitive experiences.	ME
Linguistic Dimensions			Personal Pronouns reflect self and group reflection, highlighting that an individual using varied pronouns indicates a change in perspective. Campbell and Pennebaker (2003) also suggested that pronouns indicate an individual's way of thinking and are used based on perspective. The use of various pronouns may provide insights into how individuals reflect on their use of metacognition in learning.	MK and ME
- Personal Pronouns				
- 1st person singular	i	I, me, my, myself		
- 1st person plural	we	we, our, us, lets		
- 2nd person	you	you, your, u, yourself		

LIWC Category	Abbreviations	Frequently Used Exemplars	Relationship to Metacognition	Metacognitive Component
- 3rd person singular	shehe	he, she, her, his		
- 3rd person plural	they	they, their, them		
Cognitive Process				
- Insights	insight	know, how, think, feel	It may capture learners' cognitive processes, problem-solving, and decision-making strategies. As J. H. Flavell (1979) indicated, knowledge about cognitive processes, as well as understanding and implementing strategies, are essential parts of metacognition.	MK and Action
- Causation	cause	how, because, make, why	Causal factors allow a deeper exploration of the cognitive processes. J. H. Flavell (1979) highlighted the need for deeply understanding one's own cognitive processes.	MK
- Discrepancy	discrep	would, can, want, could	Understanding inconsistencies facilitates analysing learners' problem-solving, critical thinking, and reassessment of their understanding.	ME
- Tentative	tentat	if, or, any, something	This may indicate uncertainty or conditional thinking, reflecting on one's own cognitive processes.	MK
- Certitude	certitude	really, actually, of course, real	The degree of certainty in metacognition reveals how individuals consider certainty, acknowledge understanding and reevaluate thoughts and strategies from previous knowledge and experiences.	MK, ME, and Action
- Differentia-tion	differ	but, not, if, or	Acknowledging the differences enables students to make more informed decisions, facilitating the assessment of one's own understanding.	MK and Action
Affect			Affective dimensions aid in understanding learners' metacognitive experiences as affect	ME
- Positive Tone	tone_pos	good, well, new, love		

LIWC Category	Abbreviations	Frequently Used Exemplars	Relationship to Metacognition	Metacognitive Component
- Negative Tone	tone_neg	bad, wrong, too much, hate	influences ME components (Gibson et al., 2016).	
- Positive Emotion	emo_pos	good, love, happy, hope		
- Negative Emotion	emo_neg	bad, hate, hurt, tired		
- Anxiety	emo_anx	worry, fear, afraid, nervous		
- Anger	emo_anger	hate, mad, angry		
- Sadness	emo_sad	:(, cry, sad		
Time Orientation			Time orientation indicates how learners leverage past experiences, understand their present circumstances and improve their decision-making process for future plans/goals.	ME, Goal, and Action
- Focus Past	focuspast	was, had, were, been		
- Focus Present	focuspresent	is, are, can		
- Focus Future	focusfutrue	will, have to, going to		

3.6 Summary

To summarise, this research employed learning analytics techniques, i.e., epistemic network analysis (ENA), process mining (PM), and natural language processing techniques (LIWC), utilising the data that were grounded in theory. Four types of data sources were considered from both as a part of this study – survey data (metacognitive awareness inventory), logs data (events logs from canvas LMS), academic performance (final scores), and students' written reflections. To address RQ1, ENA, visual (PowerBI), and statistical (SPSS) analysis was performed, implementing metacognitive awareness scores, written reflections, and final scores data. RQ2, on the other hand, was addressed by utilising PM, visual (PowerBI) and statistical (SPSS) analysis using the metacognitive awareness scores and logs data. Lastly, LIWC, as a natural language processing tool, was implemented to address RQ3 by leveraging the final scores and written reflections.

Chapter 4

Results

In this chapter, the findings from the data analysis are presented in relation to the corresponding research questions to provide clear and comprehensive insights, ensuring coherence.

4.1 Findings for Research Question 1: What are the differences between IT students with high and low final scores in terms of their metacognition?

The following sub-sections highlight the results derived from analysing the differences between high and low-score students' (as defined by their final scores) metacognition (processes), addressing research question 1.

4.1.1 Research Question 1.1.: How are metacognitive processes distributed in the written reflections of IT students with high and low final scores?

Research question 1.1 addressed the distribution of the metacognitive phenomena in high and low-score students' written reflections, implementing epistemic network analysis using the ENA web tool. The following sub-sections illustrate the network graphs and the comprehensive statistical results retrieved from the ENA web tool for high and low-score students across three subjects (IT-01, IT-02, and IT-04). It is important to note that the network graphs in Figure 13, Figure 14, and Figure 15 illustrate the comparison graph of high and low-score students' distribution of metacognitive phenomena in IT-01, IT-02, and IT-04. These figures used the codes for the metacognitive phenomena as defined in Table 7, section 3.5.2.1, following Flavell's framework. As the ENA web tool does not accept parenthesis, the goals (or tasks) and actions (or strategies) phenomena are represented as Goals.or.tasks and Actions.or.strategies (see section 2.1 to understand the interconnectedness of these terms and section 3.5.2.1 for the description of the coding components). These comparison graphs (Figure 13, Figure 14, and Figure 15) show the vertical axis (y-axis) labelled as "Week 1-10 Metacognitive Shift", which means the patterns in metacognitive activities, strategies, or reflections that have occurred over the first ten weeks of the study period. The horizontal axis (x-axis), labelled as "Reflection Pattern", refers to the ways students have reflected in the weekly written reflections on their metacognitive components. The lines between the nodes show the relationships/correlations between aspects of metacognition, and the values on these lines (in the top-right and bottom-right graphs) quantify the strength of these relationships. The thicker the line, the stronger the connection is presumed to be and vice versa. The following sub-sections present the results for high and low-score students' distribution of metacognitive phenomena for each subject.

4.1.1.1 IT-01 from Autumn 2023

According to Figure 13, for IT-01, ENA explains 31.6% of the variance in coding co-occurrences along the y-axis and 42% on the x-axis. In this ENA space, the red network appears to represent the reflection pattern for low-score students with the centroid position (0.6, 0), while the blue network represents the reflection pattern for high-score students with the centroid position (-0.6, 0).

Figure 13 also shows some major connection weights for the red and blue ENA networks (top-right and bottom-right). The connection weights range from 0-1, where 0 represents no connections between metacognitive phenomenon nodes, and 1 represents the highest connection. The network analysis shows that in the red network (low-score students), the strongest connection is between MK and ME (0.30) and the weakest in "MK - Goals.or.tasks" (0.07). However, no connection was observed between Action.or.strategies and Goals.or.tasks components in low-score students' written reflections. In contrast, high-score students (Blue) demonstrated the strongest connection between MK and ME (0.75) as well, but the weight of this connection was much stronger than low-score students (Red). However, high-score students also demonstrated the weakest connection between Action.or.strategies and Goals.or.tasks (0.06). Due to a small sample size, a Mann-Whitney (non-parametric) test was used to compare differences between high ($N_{High\ =\ 7}$) and low-score ($N_{Low\ =\ 7}$) students' distribution of metacognitive phenomena (Gibbons & Chakraborti, 2014). Along the x-axis, the test showed that the high-score students' group (Median=-0.09, N=7) was not significantly different at the alpha=0.05 level from the low-score students' group (Median =0, N=7 U=15.00, p=0.25, effect size (r)=0.39; 42% variance). Along the y-axis, the test also showed that the high-score students' group (Median =-0.07, N=7) was not significantly different at the alpha=0.05 level from the low-score students' group (Median =0, N=7 U=23.00, p=0.90, effect size (r)=0.06; 31.6% variance).

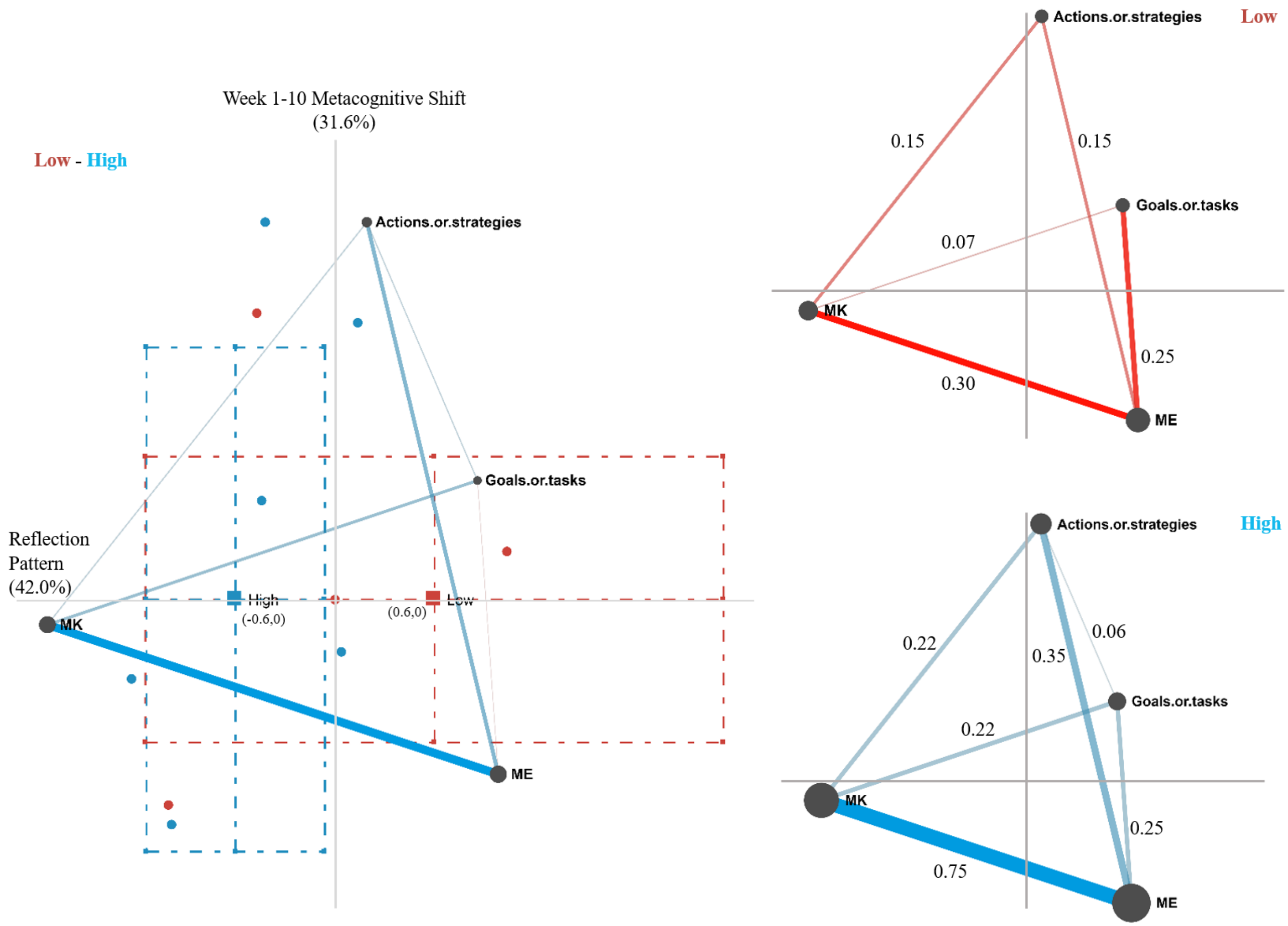


Figure 13: Left Image: Difference plot showing high (blue) and low (red)-score students' distribution of metacognitive phenomena in IT-01, Top-Right Image: Low-score students' network plot of metacognitive phenomena (IT-01), and Bottom-Right: High-score students' network plot for metacognitive phenomena (IT-01)

4.1.1.2 IT-02 from Autumn 2023

According to Figure 14, for IT-02, ENA explains 23.6% of the variance in coding co-occurrences along the y-axis and 69.0% on the x-axis. In this ENA space, the red network appears to represent the reflection pattern for low-score students with the centroid position (-2.32, 0), while the blue network represents the reflection pattern for high-score students with the centroid position (0.77, 0).

Figure 14 also shows some major connection weights for the ENA red and blue networks (top-right and bottom-right). The connection weights range from 0-1, where 0 represents no connections between metacognitive phenomenon nodes, and 1 represents the highest connection. The network analysis shows that in the red network, the strongest connection is between MK and ME (1.00) and the weakest in "MK-Goals.or.tasks" (0.10). Alternatively, high-score students (Blue) demonstrated the strongest connection in "ME-Actions.or.strategies" (1.00). However, high-score students also demonstrated the weakest connection in "MK-Goals.or.tasks" (0.10) and "Action.or.strategies–Goals.or.tasks" (0.10). Due to a small sample size, a Mann-Whitney (non-parametric) test was used to compare differences between high ($N_{High = 6}$) and low-score ($N_{Low = 2}$) students' distribution of metacognitive phenomena (Gibbons & Chakraborti, 2014). Along the x-axis, the test showed that the high-score students' group (Median=0.13, N=6) was not significantly different at the alpha=0.05 level from the low-score students' group (Median =-0.44, N=2 U=12.00, p=0.07, effect size (r)=-1.00; 69% variance). Along the y-axis, the test also showed that the high-score students' group (Median =-0.01, N=6) was not significantly different at the alpha=0.05 level from the low-score students' group (Median =0, N=2 U=6.00, p=1.00, effect size (r)=0; 23.6% variance).

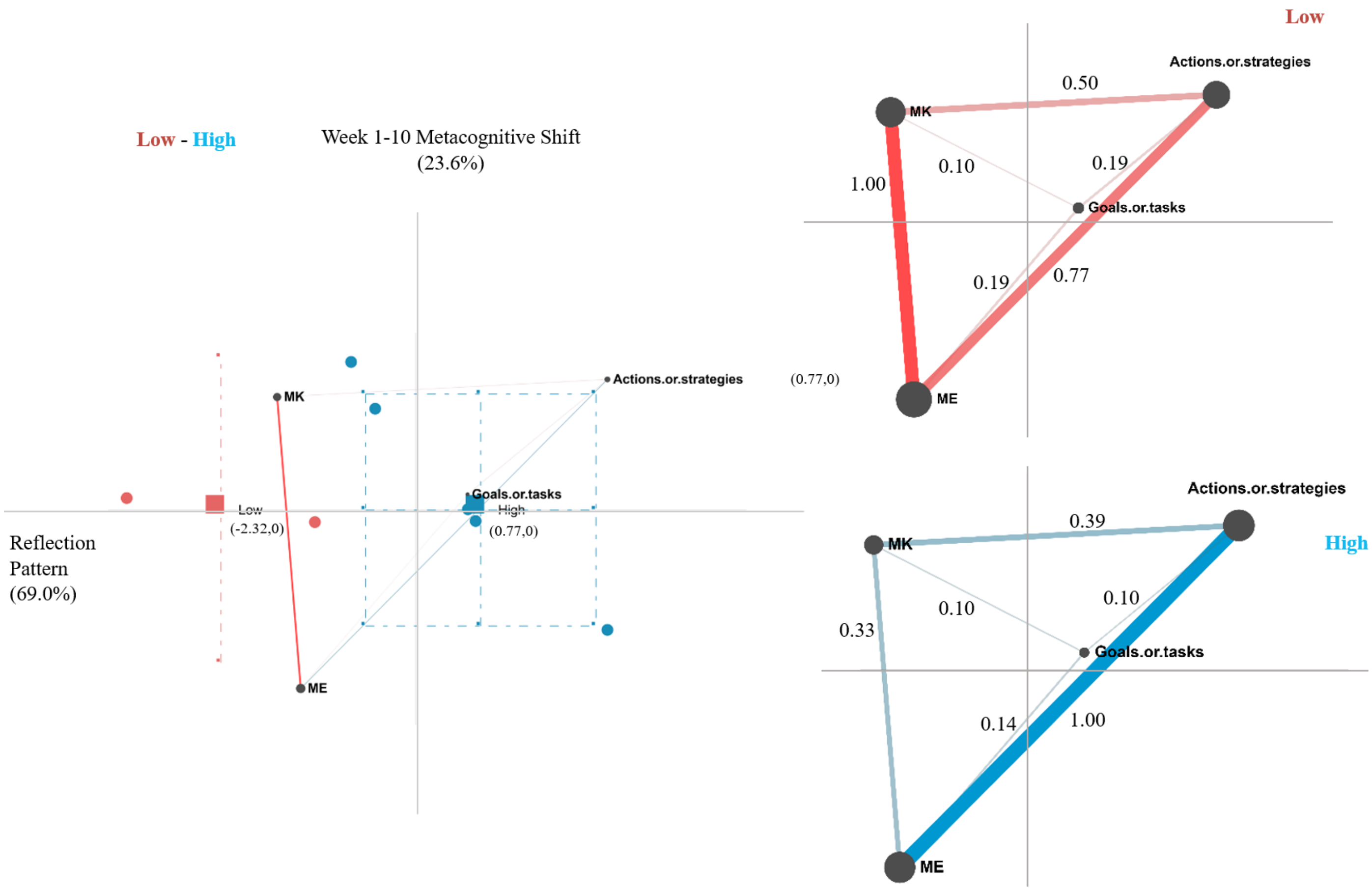


Figure 14: Left Image: Difference plot showing high (blue) and low (red)-score students' distribution of metacognitive phenomena in IT-02, Top-Right Image: Low-score students' network plot of metacognitive phenomena (IT-02), and Bottom-Right: High-score students' network plot for metacognitive phenomena (IT-02)

4.1.1.3 IT-04 from Spring 2023

According to Figure 15, for IT-04, ENA explains 33.6% of the variance in coding co-occurrences along the y-axis and 44.1% on the x-axis. In this ENA space, the red network appears to represent the reflection pattern for low-score students with the centroid position (-0.28, 0), while the blue network represents the reflection pattern for high-score students with the centroid position (0.31, 0).

Figure 15 show some major connection weights for the ENA red and blue networks (top-right and bottom-right). The connection weights range from 0-1, where 0 represents no connections between metacognitive phenomenon nodes, and 1 represents the highest connection. The network analysis shows that in the red network, the strongest connection is between MK and ME (0.55) and the weakest in “Action.or.strategies–Goals.or.tasks” (0.28). Alternatively, high-score students (Blue) demonstrated the strongest connection in MK and ME (0.48) as well. However, high-score students also demonstrated closer connections in “MK-Actions.or.strategies” (0.43) and “ME-Actions.or.strategies” (0.44). Due to the small sample size, a Mann-Whitney (non-parametric) test was used to compare differences between high ($N_{High\ =\ 10}$) and low-score ($N_{Low\ =\ 9}$) students’ distribution of metacognitive phenomena (Gibbons & Chakraborti, 2014). Along the x-axis, the test showed that the high-score students’ group (Median=-0.02, N=10) was not significantly different at the alpha=0.05 level from the low-score students’ group (Median =0.09, N=9 U=24.00, p=0.09, effect size (r)=0.47; 44.1% variance). Along the y-axis, the test also showed that the high-score students’ group (Median =0.05, N=10) was not significantly different at the alpha=0.05 level from the low-score students’ group (Median =-0.03, N=9 U=52.00, p=0.60, effect size (r)=-0.16; 33.6% variance).

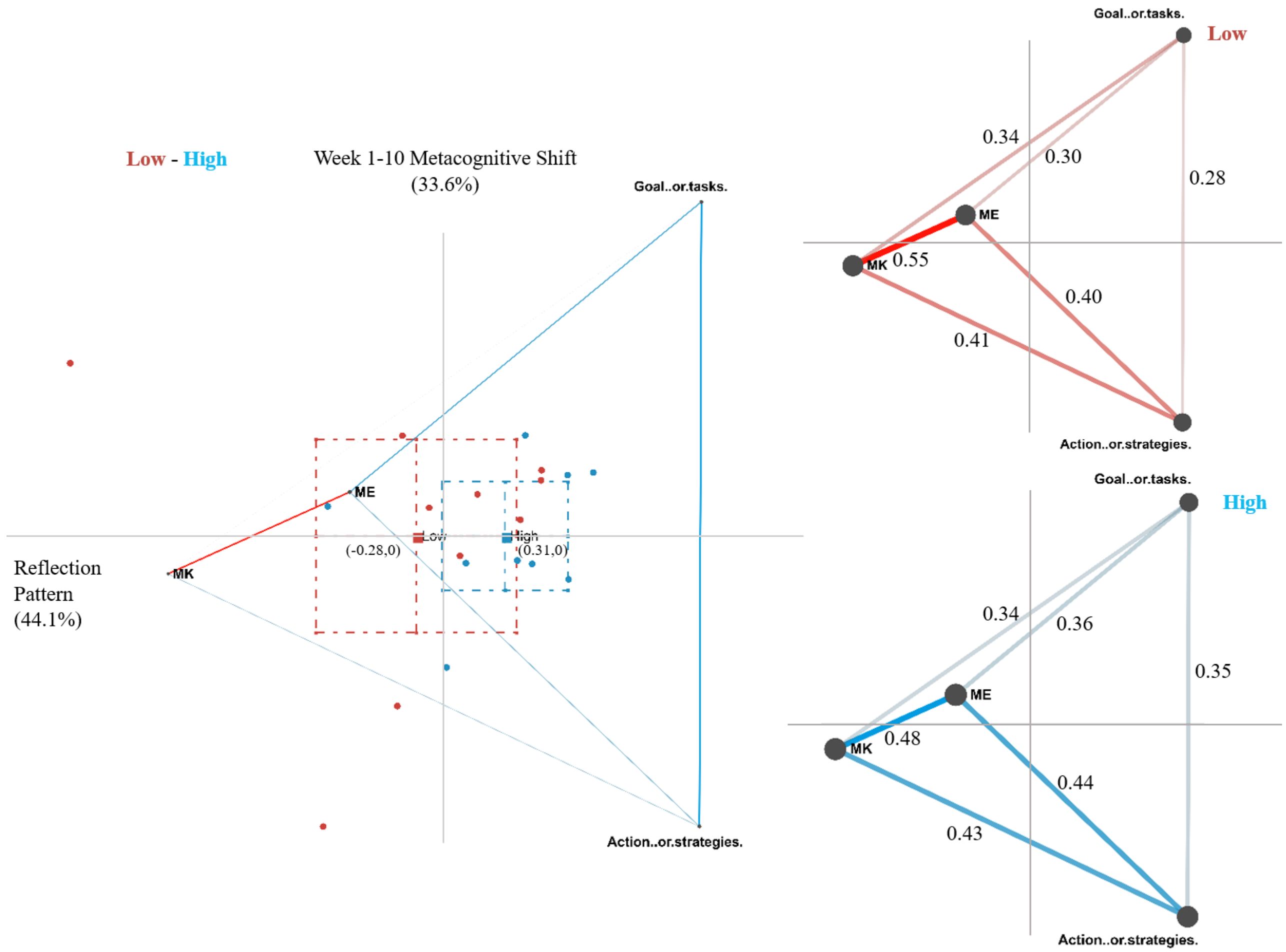


Figure 15: Left Image: Difference plot showing high (blue) and low (red)-score students' distribution of metacognitive phenomena in IT-04, Top-Right Image: Low-score students' network plot of metacognitive phenomena (IT-04), and Bottom-Right: High-score students' network plot for metacognitive phenomena (IT-04)

4.1.2 Research Question 1.2.: What is the difference between high and low-score IT students' metacognitive awareness?

RQ1.2. addressed the differences between high and low-score students' metacognitive awareness using PowerBI for visualisations and SPSS for statistical analysis. The following sub-sections provide a granular visualisation of the differences (in high and low-score students) in the components of metacognitive awareness, i.e., knowledge of cognition (declarative knowledge, procedural knowledge, and conditional knowledge) and regulation of cognition (planning, information management, monitoring, debugging, and evaluation) across all three subjects (IT-01, IT-02, and IT-04). The visuals provide a comprehensive view of the differences between high and low-score students' metacognitive awareness scores (MAI score). However, the Mann-Whitney test was performed (due to the small sample size - see section 3.5.1) to understand the significance of the differences between high and low-score students' metacognitive awareness.

4.1.2.1 IT-01 from Autumn 2023

Figure 16 represents the average score for knowledge of cognition and regulation of cognition along the y-axis and final score groups divided into high and low-score students along the x-axis for IT-01. High-score students had a higher average knowledge of cognition (77.71) and regulation of cognition (139.43) compared to low-score students (knowledge of cognition = 74.50 and regulation of cognition = 135.50).

Table 11 and Table 12 contain a more detailed analysis of the components of knowledge and regulation of cognition (the lighter green represents the higher value between the groups, and the light grey represents the same value for the two groups of students). High-score students had higher average scores in declarative knowledge (high-score = 37.143; low-score = 34.5), conditional knowledge (high-score = 23.143; low-score = 21.5), and debugging (high-score = 23.571; low-score = 21.5) (see Table 11). On the other hand, low-score students had higher average scores in procedural knowledge (high-score = 17.429; low-score = 18.5), planning (high-score = 30; low-score = 31.5), information management (high-score = 43; low-score = 44), and monitoring (high-score = 29.143; low-score = 30.5). Evaluation scored 25 in both groups of students. However, with a sample size of N=9, the Mann-Whitney test with statistics of 7.000 and two-sided exact significance (p-value) of 1.000 for "knowledge of cognition" and a Mann-Whitney test with statistics of 7.500 and two-sided exact significance (p-value) of 0.883 for "regulation of cognition", suggested no significant differences between high and low-score students' metacognitive awareness scores (MAI score).

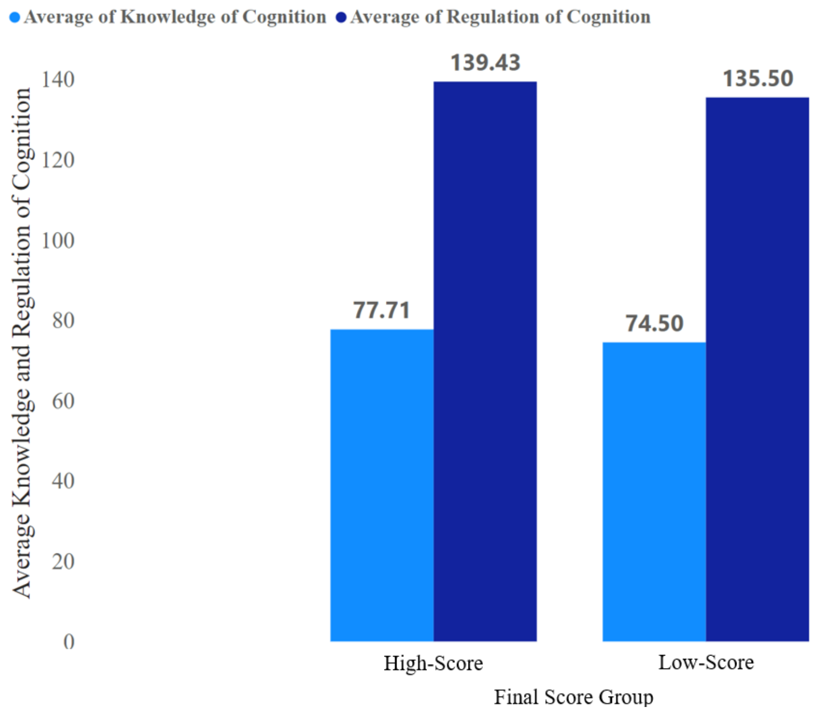


Figure 16: Differences between High and Low-score Students' Average Knowledge and Regulation of Cognition (IT-01)

Table 11: Difference Between High and Low-score Students' Average Knowledge of Cognition (IT-01)

Performance	Declarative Knowledge	Procedural Knowledge	Conditional Knowledge
High-score	37.143	17.429	23.143
Low-score	34.5	18.5	21.5

Table 12: Difference Between High and Low-score Students' Average Regulation of Cognition (IT-01)

Performance	Planning	Information Management	Monitoring	Debugging	Evaluation
High-score	30	43	29.143	23.571	25
Low-score	31.5	44	30.5	21.5	25

4.1.2.2 IT-02 from Autumn 2023

Figure 17 represents the average score of knowledge of cognition and regulation of cognition for high and low-score students from IT-02. High-score students had a higher average knowledge of cognition (65.83) and regulation of cognition (133.17) compared to low-score students (knowledge of cognition = 54.50 and regulation of cognition = 100.00). The difference in average regulation of cognition between the two groups is more evident than the difference in knowledge of cognition (see Figure 17).

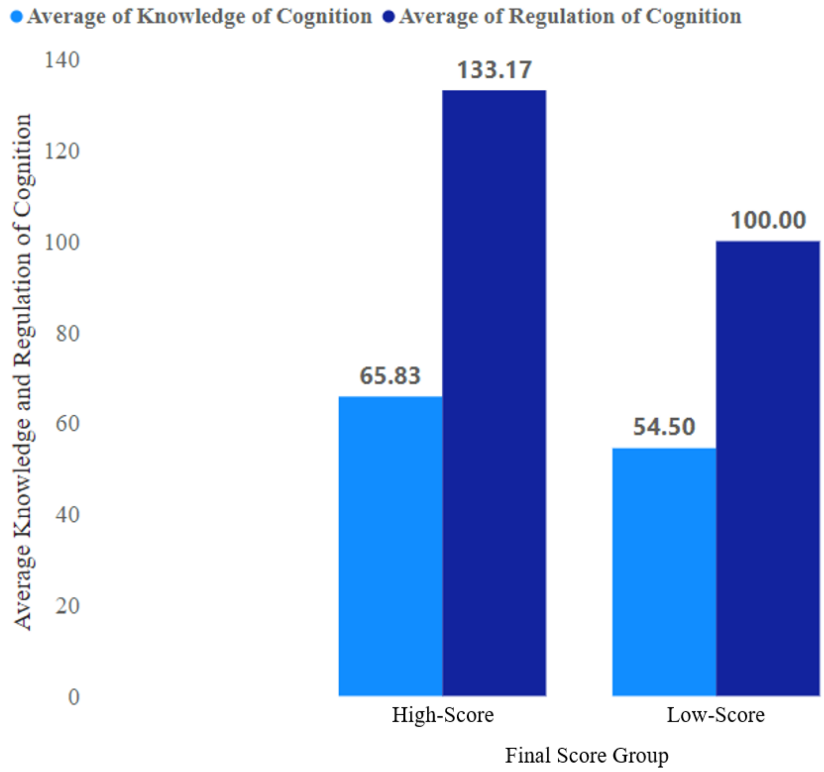


Figure 17: Differences between High and Low-score students' Average Knowledge and Regulation of Cognition (IT-02)

The following Table 13 and Table 14 provide a detailed analysis of the components of knowledge and regulation of cognition (the lighter green represents the higher value between the groups) of the IT-02 cohort. High-score students had higher average scores in all the components of knowledge of cognition - declarative knowledge (high-score = 31.83; low-score = 29), procedural knowledge (high-score = 14.67; low-score = 10.5), and conditional knowledge (high-score = 19.33; low-score = 15).

Table 13: Difference Between High and Low Performing Students' Average Knowledge of Cognition (IT-02)

Performance	Declarative Knowledge	Procedural Knowledge	Conditional Knowledge
High-score	31.83	14.67	19.33
Low-score	29	10.5	15

Additionally, high-score students from this cohort also had higher average scores in all the components of regulation of cognition – planning (high-score = 25.17; low-score = 19.5), information management (high-score = 39.17; low-score = 29.50), monitoring (high-score = 26.33; low-score = 19.5), debugging (high-score = 20.33; low-score = 15.5), and evaluation (high-score = 22.17; low-score = 16). However, with a sample size of N=8, a Mann-Whitney test with statistics of 5.000 and two-sided exact significance (p-value) of 0.737 for "knowledge of cognition" and a Mann-Whitney test with statistics of 5.000 and two-sided exact significance (p-value) of 0.736 for "regulation of cognition", suggested no significant differences between high and low-score students' metacognitive awareness scores (MAI Score).

Table 14: Difference Between High and Low Performing Students' Average Regulation of Cognition (IT-02)

Performance	Planning	Information Management	Monitoring	Debugging	Evaluation
High-score	25.17	39.17	26.33	20.33	22.17
Low-score	19.5	29.50	19.5	15.5	16

4.1.2.3 IT-04 from Spring 2023

Figure 18 represents the average score of knowledge of cognition and regulation of cognition for high and low-score students from IT-04. High-score students had a higher average knowledge of cognition (69.67) and lower regulation of cognition (131.89) compared to low-score students (knowledge of cognition = 68.80 and regulation of cognition = 138.20).

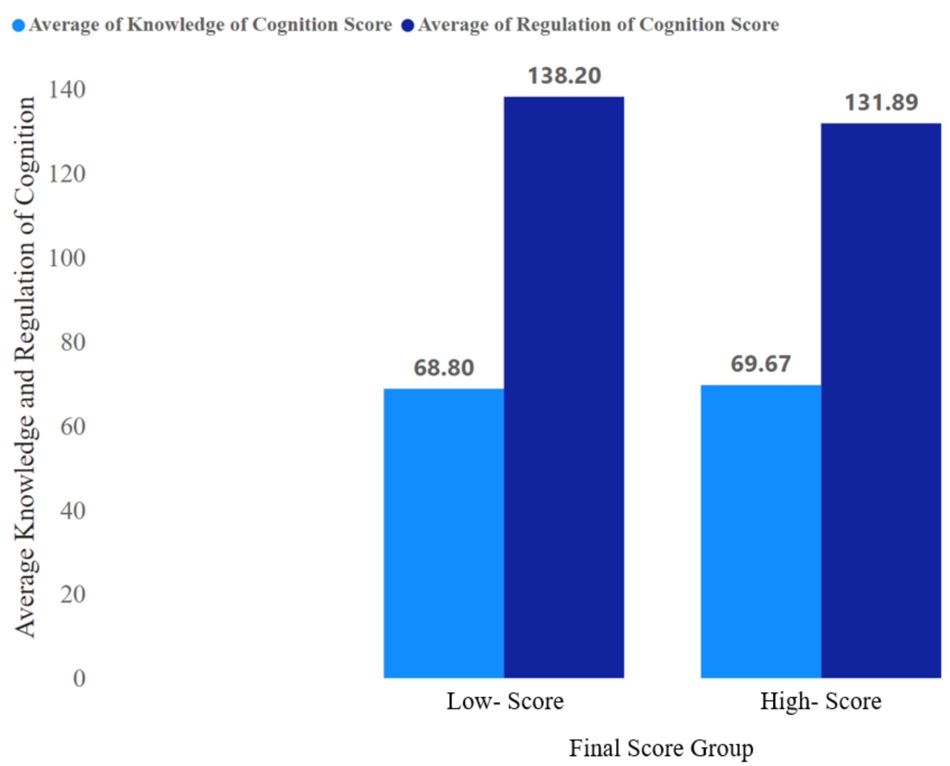


Figure 18: Differences between High and Low-score Students' Average Knowledge and Regulation of Cognition (IT-04)

The following Table 15 and Table 16 illustrate a comprehensive breakdown of the components of knowledge and regulation of cognition (the lighter green represents the higher value between the groups) of IT-04. High-score students had higher average scores in procedural knowledge (High-score = 16.44; Low-score = 15.3) from knowledge of cognition.

Table 15: Difference Between High and Low-score Students' Average Knowledge of Cognition (IT-04)

Performance	Declarative Knowledge	Procedural Knowledge	Conditional Knowledge
High-score	32.78	16.44	20.44
Low-score	32.9	15.3	20.60

Additionally, from the regulation of cognition (see Table 16), high-score students had higher average scores in planning (High-score = 27.44; Low-score = 27.10). On the other hand, low-score students had higher average scores in declarative knowledge (High-score = 32.78; Low-score = 32.9), conditional knowledge (High-score = 20.44; Low-score = 20.60), information management (High-score = 37.67; Low-score = 39.80), monitoring (High-score = 26.33; Low-score = 26.90), debugging (High-score = 19.33; Low-score = 21.10), and evaluation (High-score = 21.11; Low-score = 23.30). However, with a sample size of N=19, a Mann-Whitney test with statistics of 43.000 and two-sided exact significance (p-value) of 0.905 for "knowledge of cognition" and a Mann-Whitney test with statistics of 58.500 and two-sided exact significance (p-value) of 0.278 for "regulation of cognition", suggested no significant differences between high and low-score students' metacognitive awareness scores (MAI Score).

Table 16: Difference Between High and Low-score Students' Average Regulation of Cognition (IT-04)

Performance	Planning	Information Management	Monitoring	Debugging	Evaluation
High-score	27.44	37.67	26.33	19.33	21.11
Low-score	27.10	39.8	26.90	21.10	23.30

4.2 Findings for Research Question 2: How do semester-long metacognitive interventions have an impact on IT students' metacognition?

The following sub-sections highlight the results derived from analysing the differences in metacognition between students who experienced the intervention and those who did not, addressing research question 2.

4.2.1 Research Question 2.1.: How do IT students' pre and post-MAI scores differ between students who have experienced metacognitive interventions and those who have not?

Research question 2.1 addressed the differences in pre and post metacognitive awareness scores (Pre-MAI and Post-MAI) between students who experienced the intervention and those who did not. Figure 19 represents the visual of average pre and post metacognitive awareness scores (Pre-MAI and Post-MAI) for students who experienced interventions (IT-04). The average knowledge of cognition increased from 64.78 to 68.03 for this cohort that experienced the intervention. Similarly, their regulation of cognition also increased from 133.08 to 136.35 in their metacognitive awareness scores.

IT-04 Pre and Post Metacognitive Awareness (Experienced Intervention)

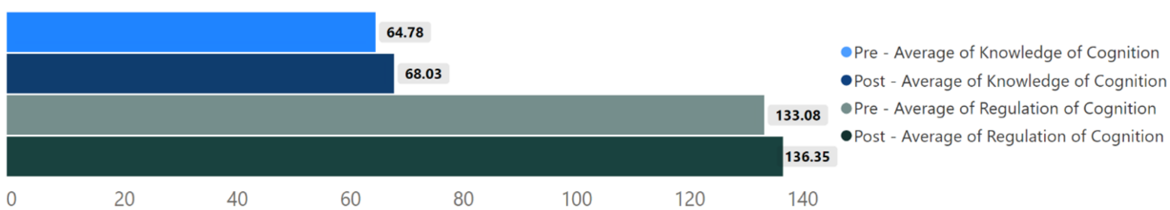


Figure 19: Average Metacognitive Awareness scores of students who experienced the interventions (IT-04)

Alternatively, students from IT-05, from Figure 20, did not receive the intervention during the semester. However, similar to IT-04, their self-reported metacognitive awareness score increased for both knowledge of cognition (from 63.33 to 67.67) and regulation of cognition (132.27 to 139.80).

IT-05 Pre and Post Metacognitive Awareness (No Intervention)

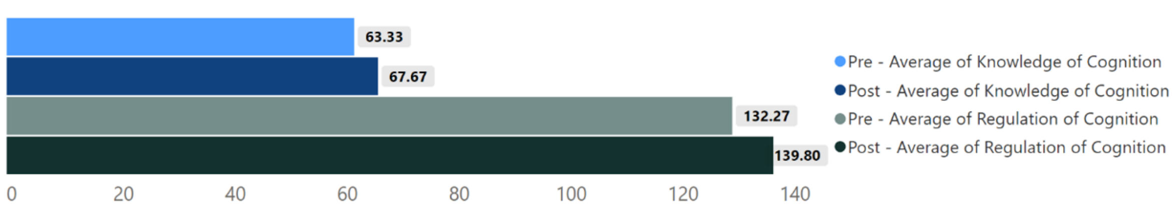


Figure 20: Average Metacognitive Awareness scores of students who did not experience the interventions (IT-05)

Table 17 below represents a more granular analysis of the components of knowledge of cognition scores (both pre and post) between IT-04 and IT-05 (see the following Table 19 for significance). The light green filled-in cell represents a higher value in the post components of knowledge of cognition, comparing IT-04 and IT-05. For the declarative knowledge component, both

IT-04 and IT-05 demonstrated increase in their score from pre (IT-04 = 30.78; IT-05 = 30.27) to post (IT-04 = 32.00; IT-05 = 31.27). However, students who received interventions (IT-04) had higher declarative knowledge scores at the end of the semester. Similarly, for procedural knowledge, both IT-04 and IT-05 demonstrated increase in their score from pre (IT-04 = 18.83; IT-05 = 14.27) to post (IT-04 = 20.13; IT-05 = 15.87). This suggests that students who received interventions reported to have higher procedural knowledge. For conditional knowledge, on the other hand, although both IT-04 and IT-05 demonstrated an increase in their score from pre (IT-04 = 15.18; IT-05 = 18.80) to post (IT-04 = 15.90; IT-05 = 20.53) students who did not receive the intervention (IT-05), reported to have higher conditional knowledge at the end of the semester.

Table 17 Differences in average pre and post "knowledge of cognition" scores between IT-04 and IT-05

	Declarative Knowledge		**Procedural Knowledge**		**Conditional Knowledge**	
	IT-04	IT-05	IT-04	IT-05	IT-04	IT-05
Pre	30.78	30.27	18.83	14.27	15.18	18.80
Post	32.00	31.27	20.13	15.87	15.90	20.53

Conjointly, Table 18 illustrates the differences in the IT-04 and IT-05 cohorts' average scores of the components of regulation of cognition (see Table 19 for significance). The light green filled-in cell represents higher average post-MAI scores, comparing IT-04 and IT-05. Both IT-04 and IT-05 reported to have an increased score in planning from pre (IT-04 = 26.55; IT-05 = 26.27) to post (IT-04 = 27.48; IT-05 = 27.47), but students who received metacognitive interventions reported to have higher scores in planning at the end of the semester. Interestingly, students who did not receive any interventions reported having higher scores in information management, monitoring, debugging, and evaluation. For example, for information management, both IT-04 and IT-05 reported having an increased score from pre (IT-04 = 38.60; IT-05 = 38.40) to post (IT-04 = 39.05; IT-05 = 39.80), having higher scores in students of IT-05 at the end of the semester. For debugging, IT-05 reported to have an increased score in debugging, and IT-04 reported to have decreased score from pre (IT-04 = 20.23; IT-05 = 19.67) to post (IT-04 = 19.93; IT-05 = 20.93) having higher score in IT-05 at the end of the semester. In evaluation, a similar pattern was noticed; students from both of these subjects reported having increased awareness of evaluation from pre (IT-04 = 21.40; IT-05 = 21.60) to post (IT-04 = 22.75; IT-05 = 24.07), suggesting higher awareness in evaluation in students who did not receive any interventions.

Table 18 Differences in average pre and post regulation of cognition scores between IT-04 and IT-05

	Planning		**Information Management**		**Monitoring**		**Debugging**		**Evaluation**	
	IT-04	IT-05	IT-04	IT-05	IT-04	IT-05	IT-04	IT-05	IT-04	IT-05
Pre	26.55	26.27	38.60	38.40	26.30	26.33	20.23	19.67	21.40	21.60
Post	27.48	27.47	39.05	39.80	27.15	27.53	19.93	20.93	22.75	24.07

However, running a non-parametric Kruskal-Wallis test (represented in Table 19) suggested that there were no significant differences in both pre and post metacognitive awareness scores between students who experienced interventions (IT-04) and students who did not (IT-05), as the significance values for both knowledge of cognition (pre = 0.466 and post = 0.925) and regulation of cognition (pre = 0.684 and post = 0.400) were above the conventional alpha level (0.05). The reported test statistics values also support the no significant differences between these groups of students (IT-04: students who experienced intervention and IT-05: those who did not).

Table 19 Significance of pre and post metacognitive awareness scores between IT-04 and IT-05

	Knowledge of Cognition		**Regulation of Cognition**	
	Significance	**Test Statistic**	**Significance**	**Test Statistic**
Pre	0.466	0.531	0.684	0.165
Post	0.925	0.009	0.400	0.708

4.2.2 Research Question 2.2.: Are there any differences in the temporal patterns in students' learning traces between IT students who have experienced metacognitive interventions and those who have not?

Research question 2.2 addressed the differences in the temporal patterns in students' learning traces between students who experienced metacognitive interventions (IT-04) and students who did not (IT-05). The following sub-sections illustrate the results of these process models and their activity statistics. The results from this analysis were performed following the analytical framework (see section 3.5.4.1). Table 8 and Table 9 in the earlier section, provided a comprehensive view of this coding. Both low-level mapping and high-level coding were selected to represent the "Activity" for comprehensive and granular analysis (see Appendix G for steps followed in Disco). The visuals in this subsection were retrieved from the Disco process mining software. To keep the visuals authentic, a mix of cutouts and full versions of the original visuals from the Disco software are presented in this document. As the visuals of the process models had extensive scale, which could not be adequately represented in this document, the full visuals can be accessed by following an external link to a GitHub repository – *Students who received the intervention (IT-04)* and *Students who did not receive the intervention (IT-05)*. Readers of this document are highly encouraged to access these models for better visual readability. Alternatively, Appendix I contains the process models of these cohorts that need to be zoomed in for better visibility.

4.2.2.1 Comparative Differences in the Patterns

Following the highest absolute frequency of path, students who received metacognitive interventions (IT-04) started with "Subject Grade View + Evaluation", proceeded with "Subject Announcement View + Planning", then "Subject Outline View + Planning", and then moved to "Weekly Tutorial Content View + Information Management". This indicates a sequence of evaluation, planning, and information management components of regulation of their cognition (a cutout of the process model representing this sequence is illustrated in Figure 21). Students who did not receive the intervention (IT-05), on the other hand, following the highest absolute path frequency, started with "Weekly Tutorial Content View – Information Management" and proceeded with "List of Subject Assignments View' – Planning (absolute path frequency = 72), then "Subject Assignments View – Information Management" (absolute path frequency = 218), and then "Subject Grade View – Evaluation" (absolute path frequency = 63). This suggests a sequence of information management, planning, information management, and then evaluation (see Figure 22).

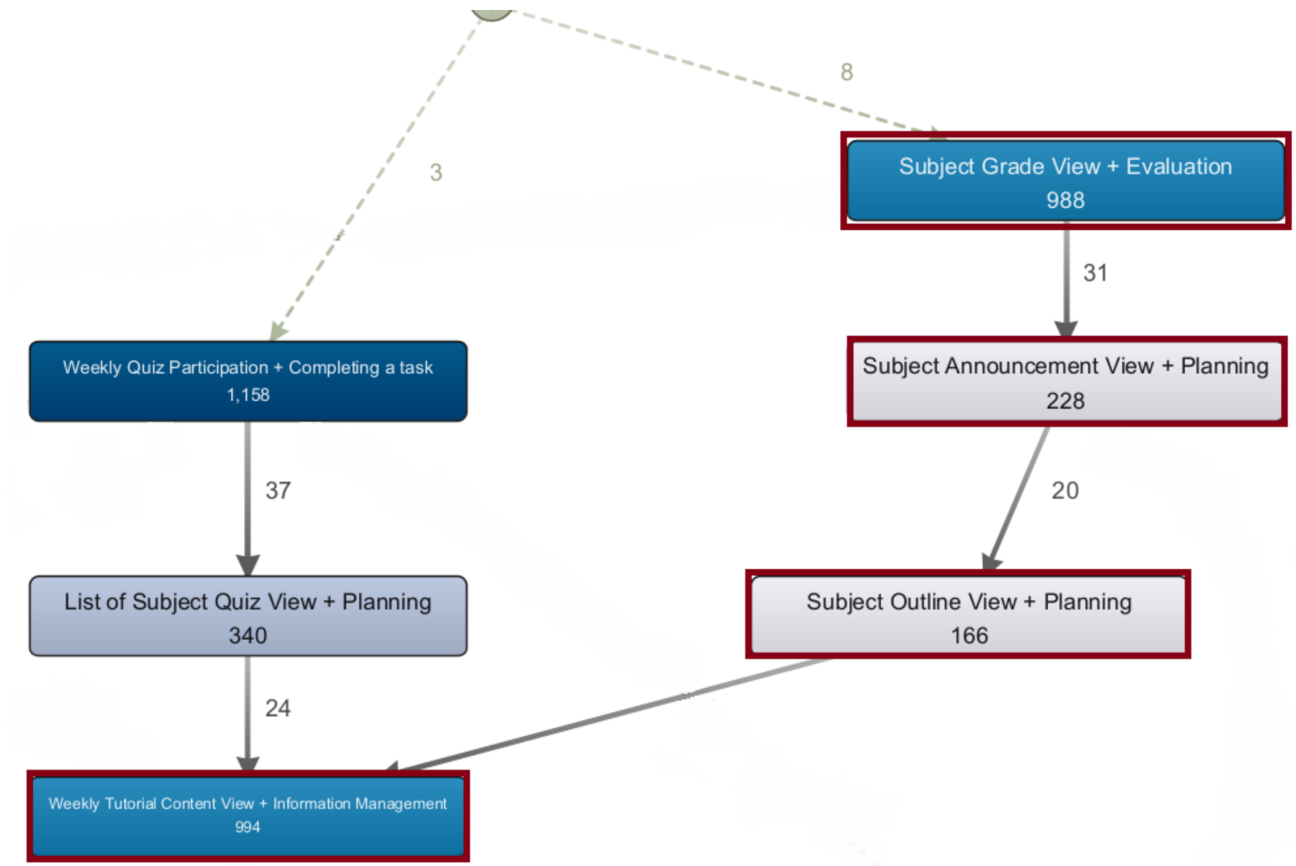


Figure 21: Illustration of sequences of activities from "Subject Grade View + Evaluation" to "Weekly Tutorial Content View + Information Management" of students who received the intervention (IT-04)

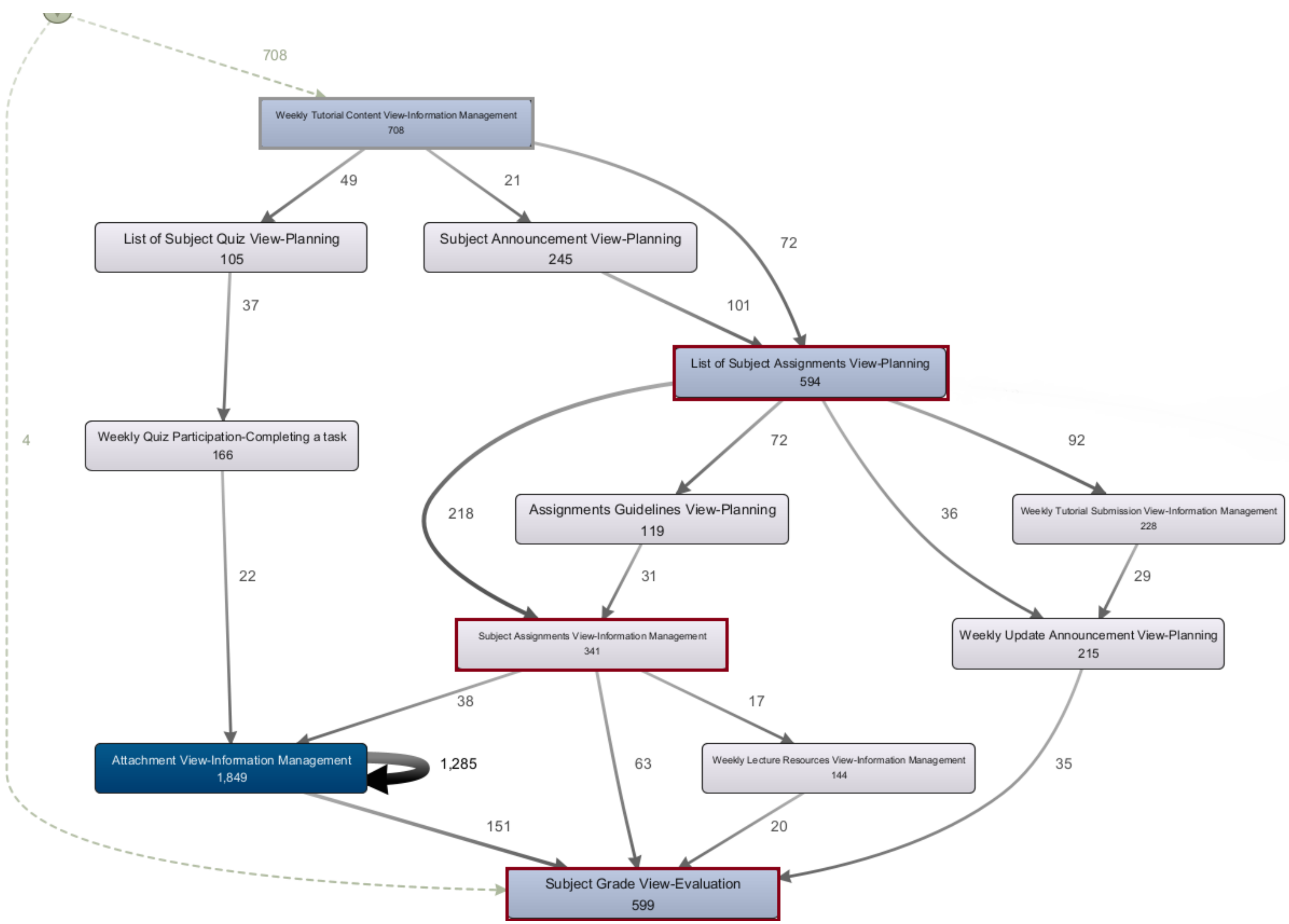


Figure 22: Illustration of sequences of activities from "Weekly Tutorial Content View – Information Management" to "Subject Grade View - Evaluation" of students who did not receive the intervention (IT-05)

It was also observed that students who received the intervention went through several phases with different absolute path frequencies (see Figure 23) before viewing the weekly tutorial content (Weekly Tutorial Content View + information management, case frequency of 994). For example, students mostly viewed attachments related to learning content (Attachment View + information management; case frequency of 611; absolute path frequency = 157). Having a lower absolute path frequency, students also viewed the "List of subject Quiz + Planning" (absolute path frequency = 24; case frequency of 340) and "Subject Outline View + Planning" (absolute path frequency = 25; case frequency of 166). This demonstrates a pattern of going through attachments related to content (Attachment View + information management), viewing the list of subject quizzes (List of Subject Quiz View + planning), and viewing the subject outline (Subject Outline View + planning) before proceeding with viewing the weekly tutorial content (Weekly Tutorial Content View – part of planning), suggesting an implementation of regulation of cognition activities. On the contrary, students who did not receive the intervention did not demonstrate any prior interaction with the subject before proceeding with interacting with the weekly tutorials (Weekly Tutorial Content View – information management, case frequency of 708) (see "*Students who did not receive the intervention*" or Appendix I).

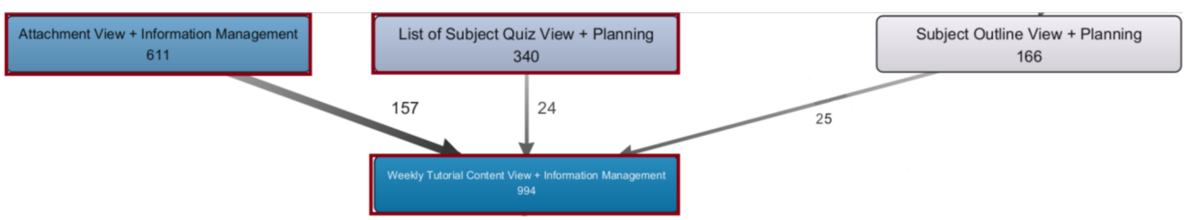


Figure 23: Illustration of connections towards "Weekly Tutorial Content View + Information Management" for students who received the intervention (IT-04)

Further differences based on "Weekly Quiz Participation" were found with respect to completing a task. Figure 24 illustrates that students from IT-04 (students who received interventions) did not demonstrate any interaction with the subject before participating in the weekly quizzes (Weekly Quiz Participation; case frequency = 1158). However, students who did not receive the interventions viewed the list of subject quizzes – "List of Subject Quiz View – Planning" (absolute path frequency = 37 and case frequency = 105) and "Weekly Tutorial Content View" – Information Management (absolute path frequency = 49 and case frequency = 708) before starting to participate in the "Weekly Quiz Participation – Completing a task" (see Figure 25).

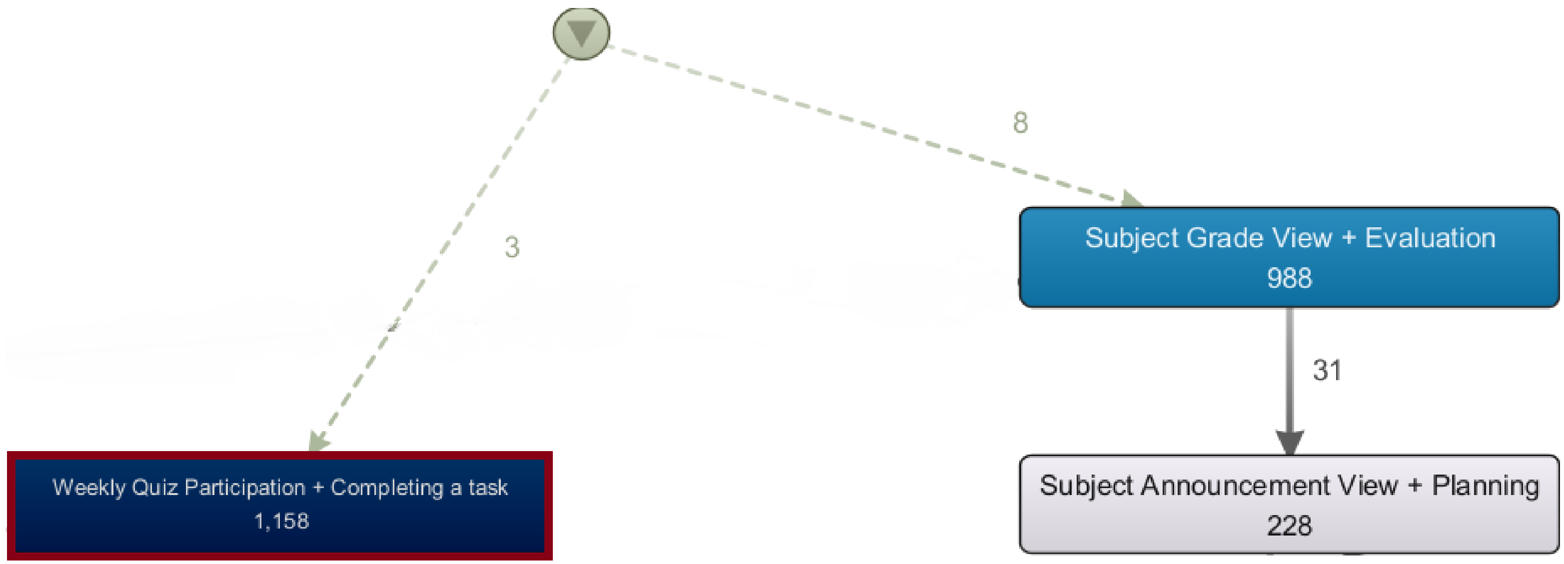


Figure 24: Illustration of highlighting no absolute frequency path before "Weekly Quiz Participation + Completing a task" of students who received the intervention (IT-04)

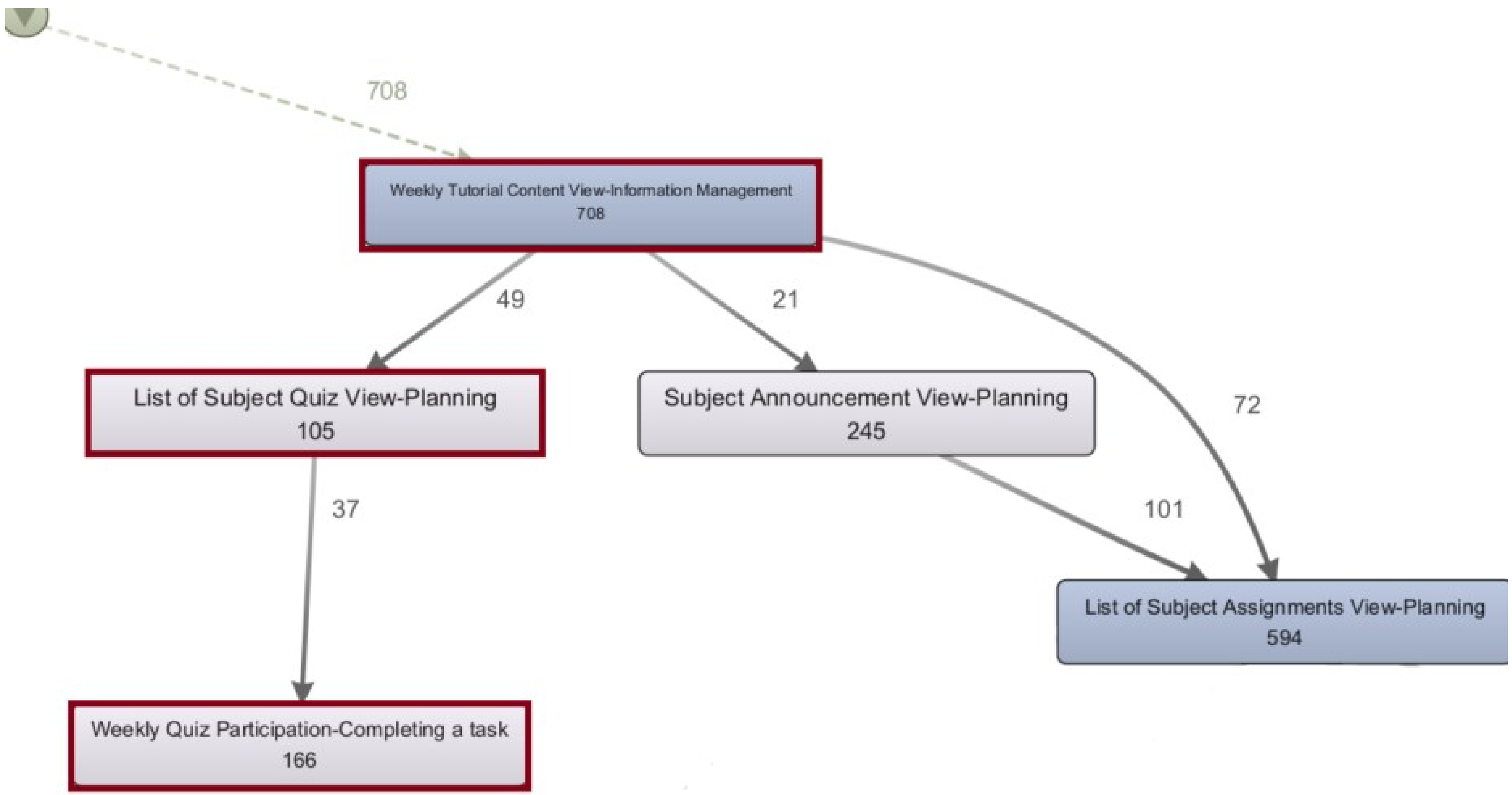


Figure 25: Illustration of sequences of activities before "Weekly Quiz Participation - Completing a task" of students who did not receive any intervention (IT-05)

Another observation was made on the interactions between "List of Subject Assignments View" (a case frequency of 1323 for IT-04 and 594 for IT-05) and its traces towards "Subject Assignments Participation" - part of completing a task (a case frequency of 135 for IT-04 and 37 for IT-05). As these interactions had an extensive scale that could not be represented even as a cutout in this document, please visit this external link, "*Students who received the intervention*", to have a complete view of the process model. Students who experienced metacognitive interventions (IT-04), starting from "List of Subject Assignments View + Planning", demonstrated the first phase of traces in "List of Subject Assignments View + Planning" → "Weekly Progress Check View + Monitoring" (absolute path frequency = 17) and "List of Subject Assignments View + Planning" → "Weekly Reflection View + Evaluation" (absolute path frequency = 99). In the next phases of traces, they demonstrated interactions of "List of Subject Assignments View + Planning" → "Weekly Reflection View + Evaluation" → "Weekly Content Overview View + Planning" → "Weekly Update Announcement View + Planning" → "Weekly Classes and Drop-in Details + Information Management" → "Weekly Tutorial Submission View + Information Management" → "Weekly Reflection Participation + Evaluation" → "Subject Assignments View + Information Management" → "Weekly Lecture Resources View + information Management" → "Subject Grade View + Evaluation" → "Subject Assignments Participation + Completing a task". This interaction, from viewing the list of subject assignments to participating/submitting the subject assignment (Planning + List of Subject Assignments View → Completing a task + Subject Assignments Participation), involves all the coded components of regulation of cognition, i.e., planning, information management, monitoring, and evaluation. For IT-05 students who did not receive the intervention (see "*Students who did not receive the intervention*" or Appendix I), on the other hand, the first phase of traces from "List of Subject Assignments View – Planning" was "List of Subject Assignments View – Planning" → "Subject Assignments View – Information Management" (absolute frequency of 218), "List of Subject Assignments View – Planning" → "Assignments Guidelines View – Planning" (absolute frequency of 72), "List of Subject Assignments View – Planning" → "Weekly Update Announcement View Planning" (absolute frequency of 36), and "Weekly Tutorial Submission View – Information Management" (absolute frequency of 92). The following sequences contain "Attachment View - Information Management", "Weekly Lecture Resources View – Information Management", "Weekly Update Announcement View-Planning", "Weekly Lecture Resources View – Information Management", "Subject Grade View-Evaluation", and "Weekly Prepare Resource-Planning". Unlike IT-04, this sequence from viewing a list of subject assignments to submitting an assignment (List of

Subject Assignments View – Planning” to “Subject Assignments Participation – Completing a task”) involved only planning, information management, and evaluation sub-components of regulation of cognition.

Additionally, IT-04 demonstrated direct paths towards monitoring (from planning) and indirect paths towards monitoring (planning and information management) (see Figure 26), but no such absolute frequency path was observed in students who did not experience metacognitive intervention (see “*Students who did not receive the intervention*” or Appendix I). Lastly, students from IT-05 demonstrated two high absolute frequency self-looped activities in “Attachment View – Information Management” (absolute path frequency = 1285) and “Weekly Prepare Resource – Planning” (absolute path frequency = 1316), which suggest more emphasis on these learning contents were given by students from this cohort (see Figure 27). However, no such self-loops were observed for students who received metacognitive interventions.

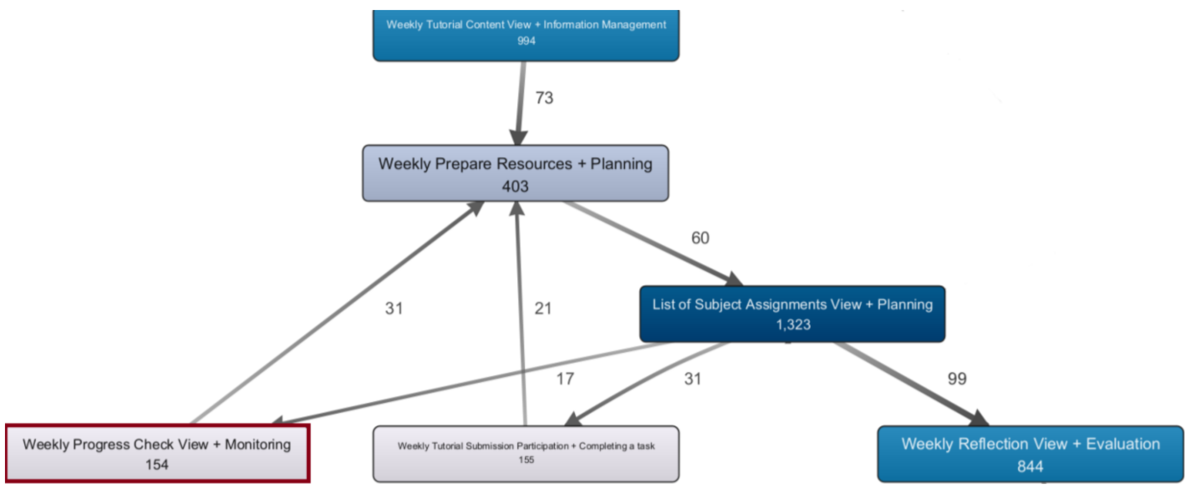


Figure 26: Presence of direct and indirect connection with "Monitoring" of students who received the intervention (IT-04)

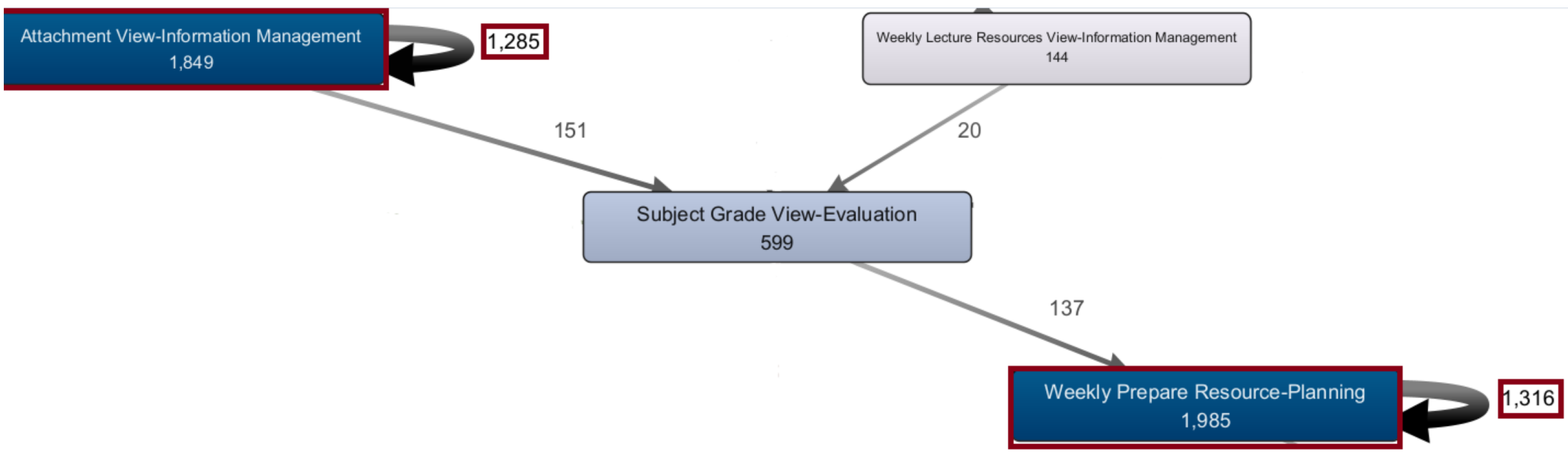


Figure 27: Illustrating two high absolute frequency self-looped activities in “Attachment View – Information Management” and “Weekly Prepare Resource – Planning” of students who did not receive any interventions (IT-05)

4.2.2.2 Comparative Differences in Activity Statistics

Comparing the activity statistics observed in both students who experienced metacognitive interventions and those who did not suggest some interesting results. Table 20 and Table 21 represent the activities of students from IT-04 and IT-05, which had a relative frequency of *more than 1%*. However, from Table 20, the traces revealed that students who received the intervention demonstrated a more balanced approach to interacting with the learning content. For example, the relative frequency of the activity in Table 20 does not show any sudden increase or decrease. Higher priority was given to List of Subject Assignments View + Planning (10.96%), followed by “Weekly Quiz Participation + Completing a task” (9.59%), “Subject Assignments View + Information Management” (8.34%), “Weekly Tutorial Content View + Information Management” (8.23%), “Subject Grade View + Evaluation” (8.18%), “Weekly Reflection View + Evaluation” (6.99%), and moving to the least to the least relative frequency “Subject Assignments Participation + Completing a task” (1.12%).

Table 20: Relative frequency of activities (above 1%) of students who experienced metacognitive interventions (IT-04)

Activity	Relative Frequency
List of Subject Assignments View + Planning	10.96%
Weekly Quiz Participation + Completing a task	9.59%
Subject Assignments View + Information Management	8.34%
Weekly Tutorial Content View + Information Management	8.23%
Subject Grade View + Evaluation	8.18%
Weekly Reflection View + Evaluation	6.99%
Attachment View + Information Management	5.06%
Weekly Tutorial Submission View + Information Management	4.39%
Weekly Reflection Participation + Evaluation	3.65%
Weekly Prepare Resources + Planning	3.34%
List of Subject Quiz View + Planning	2.82%
Avoiding Plagiarism Resources View + Information Management	2.73%
Weekly Update Announcement View + Planning	2.64%
Weekly Lecture Resources View + Information Management	2.63%
Weekly Content Overview View + Planning	2.42%
Subject Announcement View + Planning	1.89%
Weekly Classes and Drop-In Session Details + Information Management	1.77%
Subject Outline View + Planning	1.37%
Weekly Progress Check View + Monitoring	1.28%
Weekly Tutorial Submission Participation + Completing a task	1.28%

Activity	Relative Frequency
Group Presentation - Peer Feedback Participation + Evaluation	1.20%
Group Presentation - Peer Feedback View + Evaluation	1.16%
Subject Assignments Participation + Completing a task	1.12%

On the contrary, students who did not receive the intervention (IT-05) demonstrated a concentration of activity in terms of Weekly Prepare Resources – Planning and Attachment View-Information Management (see Table 21). For example, "Weekly Prepare Resource – Planning" (23.56%) and 'Attachment View – Information Management" (21.95%) had significantly higher relative frequency compared to the other activities. The following activities contain a relative frequency of 8.40% for "Weekly Tutorial Content View – Information Management", 7.11% for "Subject Grade View – Evaluation", 7.05% for "List of Subject Assignments View – Planning", 4.05% for "Subject Assignments View – Information Management", and moving to the least relative frequency of 1.01% "Avoiding Plagiarism Quiz View – Monitoring".

Table 21 Relative frequency of activities (above 1%) of students who did not experience metacognitive interventions (IT-05)

Activity	Relative Frequency
Weekly Prepare Resources - Planning	23.56%
Attachment View - Information Management	21.95%
Weekly Tutorial Content View - Information Management	8.40 %
Subject Grade View - Evaluation	7.11%
List of Subject Assignments View - Planning	7.05%
Subject Assignments View - Information Management	4.05%
Subject Announcement View-Planning	2.91%
Weekly Tutorial Submission View - Information Management	2.71%
Weekly Update Announcement View - Planning	2.55%
Avoiding Plagiarism Resources View - Information Management	2.46%
Weekly Progress Check View - Monitoring	2.35%
Weekly Reflection View - Evaluation	2.33%
Weekly Quiz Participation - Completing a Task	1.97%
Weekly lecture Resources View - Information Management	1.71%
Assignments Guidelines View - Planning	1.41%
Subject Outline View - Information Management	1.27%
List of Subject Quiz View - Planning	1.25%
Avoiding Plagiarism Quiz View - Monitoring	1.01%

Going into a more granular analysis of these traces, Figure 28 illustrates the relative frequency of the components of "regulation of cognition" implemented during interaction with the learning content by students who received metacognitive interventions (IT-04). To recall, the components of "regulation of cognition" were coded implementing the "Action library" from Table 8 and Hierarchical Library from Table 9. Starting with the component of "Information Management", the highest relative frequency was 34.36%. The gradual decrease from that point towards "Planning" was noticed to reach 29.02%. Moving from there, a slow decline to "evaluation" (21.35%) was observed. This trend continues to "Completing a task" (11.99%) and Monitoring (3.28%).

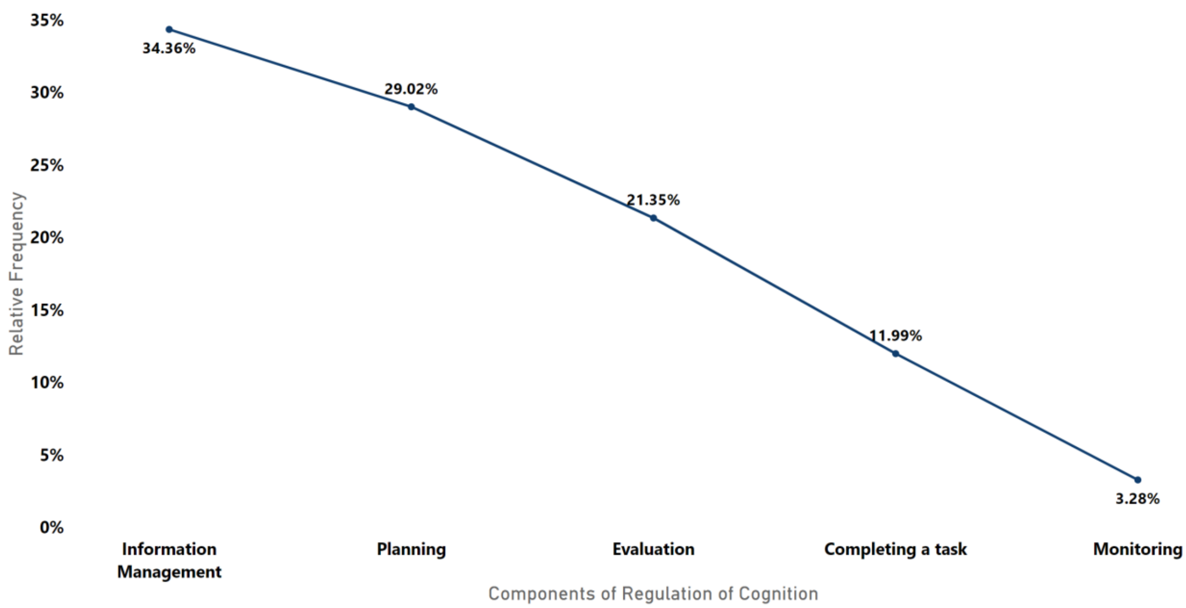


Figure 28: Relative frequency of regulation of cognition in learning traces of students who experienced metacognitive intervention (IT-04)

Figure 29 illustrates the relative frequency of the components of "regulation of cognition" implemented during interaction with the learning content by students who did not receive metacognitive interventions (IT-05). Starting with a significantly high engagement with "Information Management" at 42.90% and proceeding with a slight decrease in "Planning" (40.23%). After "planning", a steep and pronounced decrease towards "Evaluation" (10.01%) was observed. However, from evaluation, a gradual decrease was observed towards 'Monitoring" (3.75%) and "Completing a task" (3.11%). It was also observed that students who received metacognitive interventions (Figure 28) and those who did not (Figure 29), share common aspects of focusing less on "Completing a task" and "Monitoring".

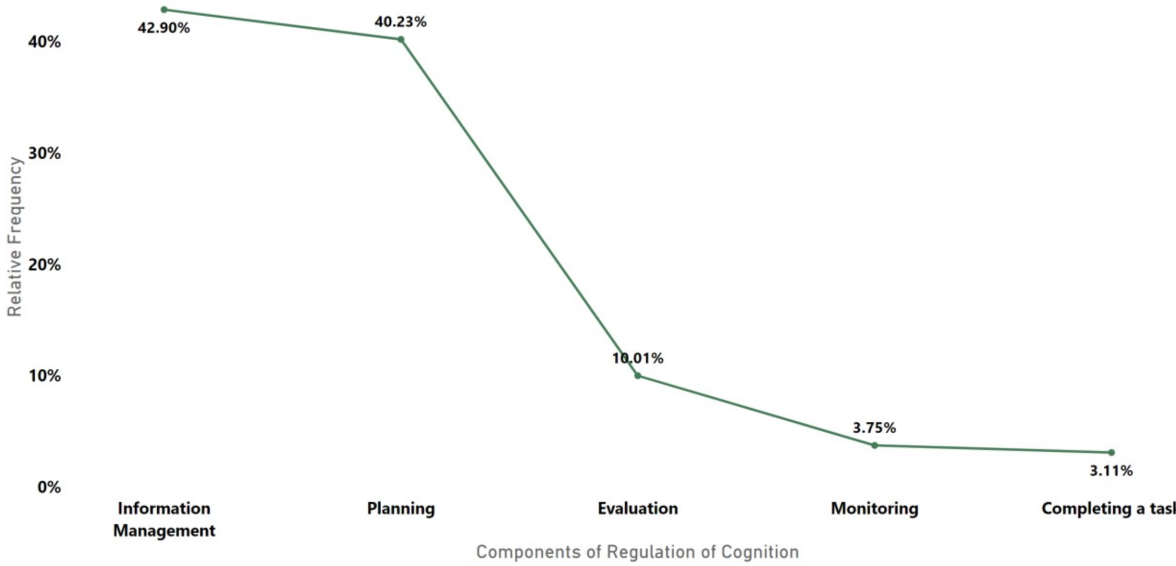


Figure 29: Relative frequency of regulation of cognition in learning traces of students who did not experience metacognitive intervention (IT-05)

4.3 Findings for Research Question 3: Which linguistic features in IT students' written reflections are significantly associated with their self-reported metacognitive awareness and final score?

Research question 3 addressed the linguistic features associated with metacognitive awareness and academic scores from students' written reflections. A number of LIWC features related to metacognition were selected for analysis (refer to Table 10). Kruskal-Wallis tests were implemented in this analysis to evaluate the systematic differences between the quartiles and any presence of LIWC features, and only significant associations were considered for further analysis. Table 22 displays only the significant linguistic features (col 1) between the MAI score quartile (col 2) and the final score quartile (col 3).

Table 22. LIWC Features in Reflective Writing: Relationships with MAI and Final Scores

LIWC Features	MAI Score Quartile		Final Score Quartile	
	Significance	Test Statistic	Significance	Test Statistic
i	0.018	10.054	0.023	9.508
we	0.002	14.938	<0.001	24.344
focuspast	0.001	15.671	<0.001	41.801
discrep	0.020	9.873	<0.001	21.431
you	0.004	13.090	-	-
shehe	0.002	14.410	-	-
tone	0.026	9.272	-	-

LIWC Features	MAI Score Quartile		Final Score Quartile	
	Significance	Test Statistic	Significance	Test Statistic
tone_neg	0.024	9.473	-	-
emo_pos	-	-	0.018	10.095
time	-	-	0.026	9.243
focuspresent	-	-	<0.001	21.776
certitude	0.029	9.010	-	-

As demonstrated in Table 22, learners' self-reported **MAI scores** differed significantly with four personal pronouns (I, we, you, and shehe), tone (significant in tone_neg), focusing on past, discrepancy, and certitude. Figure 30 illustrates the linguistic features **across different MAI groups** (Q1, Q2, Q3, and UQ). The description of the legends from this figure were described in Table 10. Students in **Q1** from the MAI score quartile group used more first-person singular pronouns (M_i = 6.39), low first-person plural pronouns (M_{we} = 0.41), low use of "shehe" (M_{shehe} = 0.03), and no second-person singular pronoun (M_{you} = 0.00). Q1 also exhibited the lowest negative tone (M_{tone_neg} = 0.20) and focused more on past experiences ($M_{focuspast}$ = 4.13), having the highest discrepancy ($M_{discrep}$ = 1.65) and certitude ($M_{certitude}$ = 0.46). For example, one student reflected:

> I know now, thanks to this week's tutorial, that I have an interest in data analysis and modelling. I wanted to try by myself to answer every question because I felt it would improve my knowledge and mastery of Excel and the basic statistical notions we worked on this week…I know now that I have a pretty good understanding of how to use the data given to me to make simple yet relevant analyses. However, I also know that I need to work more with Excel to get used to all the possibilities it gives.

Alternatively, students in **Q2** from the MAI score quartile group showed the highest focus on the past ($M_{focuspast}$ = 5.39), with a slightly higher negative tone ($M_{\text{tone\_neg}}$ = 0.23) than Q1, using significant first-person plural pronoun use (M_{we} = 0.84), moderate use of first-person singular pronoun (M_i = 5.44), lower use of second person plural pronouns (M_{you} = 0.04) compared to Q3 and UQ, and comparatively low certitude ($M_{certitude}$ = 0.33) and discrepancy ($M_{discrep}$ = 1.39) than Q1. For example, one student from Q2 reflected:

> I am currently working as an intern, and I regularly work on SQL and SSIS processes and interact with systems that follow the "ETL" framework, but I had not given a thought to which solution was better when it came to business intelligence and reporting and learning and analysing various articles and resources so I can form my own opinion was very

> rewarding, and it made me question several processes being followed… as a team I felt there was need for more coordination as we were struggling to complete the task and to do quality work so if there had been better planning ahead of time that could be solved.

Q3 from the MAI score quartile group demonstrated a moderate use of first-person pronouns (M_i, = 5.27 and M_{we} = 0.76), higher use of both second (M_{you} = 0.11) and third-person singular pronouns (M_{shehe} = 0.09) compared to Q1 and Q2, having an overall moderate negative tone (M_{neg_tone} = 0.26). These students from Q3, compared to Q1 and Q2, also demonstrated lower certitude ($M_{certitude}$ = 0.19) and discrepancy ($M_{discerp}$ = 1.37). Reflection of one student from this group (Q3) highlighting these features was:

> This week, before the tutorial, I suggested in my team's group chat that we prepare the night before and divide the tutorial tasks. I wanted our team to have some time during the tutorial to focus on assignment 4, which should also be our priority. My team agreed, and they chose the tasks they wanted to focus on. I chose question 2 because I wanted more practice using Excel to compute functions, format data, and present results. As I was doing question 2, I realised that Excel had functions just beyond your normal statistical functions to compute the average, median, mean, sum, and count … I encountered some confusion during the exercise when the monthly loan payment appeared as a negative value. I justified this as money leaving the bank account, which made sense logically. However, this caused an issue in Figure 2, question 1. My online search was inconclusive, so I asked the substitute tutor. He explained that while the negative value is technically correct, it could cause problems for Figure 2's exercise. He suggested making the loan amount negative, and following his advice worked.

On the other hand, **UQ** from the MAI score quartile group had the highest negative tone (M_{tone_neg} = 0.42) and quite a comparatively balanced focus on the past ($M_{focuspast}$ = 4.08). Students from this quartile also demonstrated the lowest level of discrepancy ($M_{discrep}$ = 1.06), a comparatively moderate certitude ($M_{certitude}$ = 0.37) while using first, second, and third personal pronouns (M_i = 5.63, M_{we} = 0.75, M_{you} = 0.14, M_{shehe} = 0.01). One of the examples of reflections highlighting these features is presented below. The average word counts for each MAI score quartile were - Q1: 180 words, Q2: 202, Q3: 260, and UQ: 197.

I like to have this kind of exercise in the class. I believe those kinds of activities can help me improve my data analysis skills and learn new data analysis techniques. I wish I attended this class last semester so I might get that job by knowing how to use the pivot tables. I especially appreciate the emphasis on following instructions for basic analytics on the dataset and gaining practical experience with the new knowledge we've acquired from school.

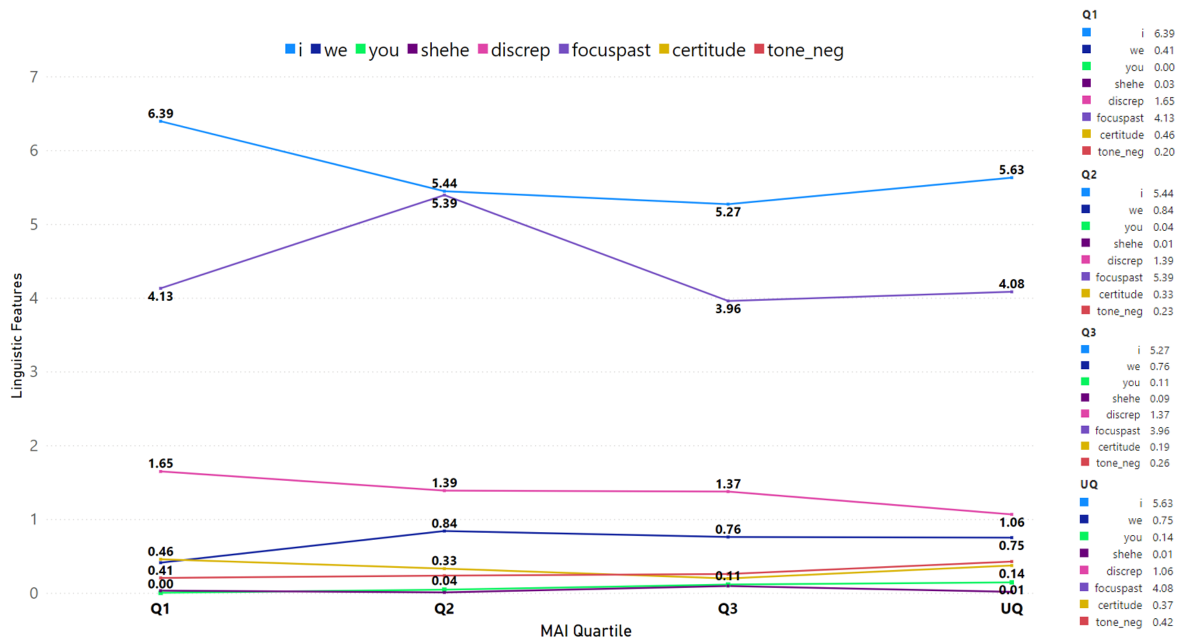


Figure 30. Linguistic features in students' reflective writing across four MAI score groups

Referring to Table 22 again, features that were found to differ significantly according to students' **academic performance (final scores)** from their written reflections were personal pronouns (i and we), positive emotion (emo_pos), focus past (focuspast), focus present (focuspresent), and discrepancy (discrep). Figure 31 highlights the significant linguistic features across different **final score quartiles** (Q1, Q2, Q3, and UQ). **Q1** from the final score quartile group emphasised relatively close focus on past ($M_{focuspast}$ = 3.38) and present experiences ($M_{focuspresent}$ = 3.44), moderately illustrating positive emotions (M_{emo_pos} = 0.40), with the highest self-focus (M_i = 6.10) and higher demonstration of group-related words (M_{we} = 0.61) (compared to Q1 and Q2). **Q2** from the final score quartile group, on the other hand, showcased a higher inclination for present ($M_{focuspresent}$ = 3.90) and past ($M_{focuspast}$ = 3.61) experiences compared to Q1. Additionally, students from this group also demonstrated the lowest positive emotions (M_{emo_pos} = 0.33) and applied the lowest first-person singular (M_i = 5.08) and plural pronouns (M_{we} = 0.48). Example of reflection highlighting these features from Q1 and Q2:

> While in this learning process, I participated in the group discussion and introduced myself and in the case study, I looked up and provided answers. During the speaking session, although we were speaking on behalf of our group, I prepared answers privately in case I could speak when no one answered. When, in fact, someone in our group wanted to speak, I listened to her carefully.

Q3 from the final score quartile group used a mixture of self-reflection (M_i = 6.08) and group reflection (M_{we} = 0.57). This group also showcased a higher positive emotion (Memo_pos = 0.54) and the lowest level of discrepancy (Mdiscrep = 0.95) while focusing moderately on the past ($M_{focuspast}$ = 5.44). Lastly, the **UQ** (upper quartile) from the final score quartile group, in their written reflection, used a combination of group ("we") and self-reflections ("i") while having higher "we" (M_{we} = 1.13) compared to other quartiles, but comparatively moderate focus on self (M_i = 5.37). However, students in UQ also demonstrated the same level of positive emotion (M_{emo_pos} = 0.54) as Q3, while highly focusing on the past ($M_{focuspast}$ = 5.48), the lowest focus on the present ($M_{focuspresent}$ = 2.57), and overall moderate discrepancy ($M_{discrep}$ = 1.46). An example of reflection highlighting these features from Q3 and UQ is presented below. Average word counts for each final score quartile were - Q1: 186 words, Q2: 193, Q3: 205, and UQ: 256.

> I would like to believe I am not a beginner at Excel and have a little more than basic knowledge of Excel and its functions. Before coming to the lecture, I had read about OLTP and OLAP queries to build on my knowledge from this week's lecture. OLTP queries are more immediate for everyday tasks and operations. OLAP is more comprehensive and structured for analysing data… For OLAP, we had to do a pivot table; I went through the help URL given in the tutorial exercise to refresh my memory, after which it was fairly easy. Overall, the exercise was fun to do as it was something practical, unlike other questions and previous tutorials where we had to write theoretical answers. All of us at the table had different levels of Excel knowledge, so we had a good time discussing our suggestions on how to approach the questions. All of us solved it and then discussed our answers, reasoning, and the steps we took. This has been my favourite question since the course started.

Figure 31. Linguistic features in students' reflective writing across four Final score groups

4.4 Summary

This chapter presents the results from the analysis of IT students' metacognition. No significant differences were observed between high and low-score students' metacognition (processes) across subjects. However, different patterns in the metacognitive phenomena were observed between these two groups (high and low-score students) within different subjects. Additionally, students who experienced the intervention had higher interaction with the learning contents, having a higher presence of regulatory components of metacognition compared to students who did not experience the intervention. Moreover, certain linguistic features (e.g., personal pronoun, time orientation, tone, emotion, and discrepancy) were significantly associated with students' metacognitive awareness and their academic performance (final scores).

Chapter 5

Discussion

5.1 Differences in High and Low-score IT Students' Metacognition

RQ1 addressed the differences in high and low-score IT students' metacognition (processes). The analytical goal of this research question was to understand, during a ten-week period of student reflective writing, if the distribution of metacognitive phenomena was different between the two groups (high and low scores). Contrary to what one may expect, Mann-Whitney tests suggested no significant difference between high and low-score students' (1) distribution of metacognitive phenomena within their written reflections and (2) in their self-reported metacognitive awareness scores in all three cohorts (IT-01, IT-02, and IT-04) (see section 3.3 for subject details, section for reflection coding 3.5.2.1, and section 4.1 for results). Results align with a study by Dent and Koenka (2016) and Veenman et al. (2006) demonstrating that offline (e.g. self-reported questionnaires, self-reported strategy use) measures of metacognition were not strongly correlated with academic performance. This could be due to the constraints of implementing a retrospective self-report, where memory and distortions might affect the association between written metacognitive reflections and actual academic performance (Dent & Koenka, 2016). However, a further comprehensive discussion of the findings is presented below.

Along both axes in the ENA network model (see section 4.1), the reflective pattern (x-axis) and week 1-10 metacognitive shift (y-axis) did not demonstrate any significant difference between high and low-score IT students. Even though there was no statistically significant difference, it is essential to comprehend the variation in network weights between these two groups of students. For example, in the ***IT-01 cohort***, MK-ME network weight was higher in high-score students, indicating a stronger connection in their metacognitive knowledge and experiences. This suggests that high-score students from this cohort have an understanding of their own cognitive processes and can effectively engage in reflecting on internal responses to these processes. For example, one high-score student from ***IT-01*** reflected:

> I personally have always struggled with programming subjects as I feel it is not my strongest suit...Moreover, I loved using Google Collab as it was a tool I had never used before, and it was easy to use. I have learnt how EDA can be simplified using Python and how data can be collected, analysed and simplified through Python commands.

The reflection of this student demonstrates the MK-ME connection by recognising weaknesses in programming, understanding strategies required to perform a certain task (MK), and expressing experiences with learning (ME). In contrast, low-score students of this cohort (***IT-01***) also demonstrated the strongest weighted connection in MK-ME among all the other connections. For example:

> It was hard to approach the blog, and I found that there was not enough guidance when trying to write the blog. Felt like there should be examples of texts just so we are able to understand the outcome that is expected of us. It was hard to complete the tutorials. Some of the information was not highlighted enough; it was a struggle to complete the information or work required of us as it was vague.

MK-ME connection from this reflection of the low-score student reflects the student's capability to identify particular aspects that are causing difficulties in learning (MK) and the resulting feeling of inadequacy while performing the task (ME). No connections between goals (or tasks) and actions (or strategies) were found in low-score students, but a light connection was found in high-score students. Alternatively, low-score students of the ***IT-02 cohort*** demonstrated the strongest MK-ME connection as well, suggesting awareness of their own cognitive (MK) and internal responses to these processes (ME). For example, one student reflected:

> I found it very hard to do the assessment as it was a combination of two topics. I understand it's not supposed to be easy, but I would rather learn and be assessed on each topic individually and then get taught how to use both methods at the same time.

This example showed an understanding of one's own cognitive process and experience related to the task. On the contrary, high-score students from ***IT-02*** demonstrated the strongest connection in ME-Actions or strategies, suggesting that students from this score group are translating their experiences into actionable strategies. For example, one high-score student from the ***IT-02 cohort*** reflected:

> This was the hardest lab so far. I struggled with grasping the concepts and ordering them in my head, but once I went through the readings a few times, I got there in the end. I had to go to a lab and clarify some random questions about "this". I still don't feel like I thoroughly understand OOP, but I think if I keep on reading and practising, I'll be able to get there. I definitely struggled with the reversed OO roleplay encounter because I wasn't making a weapon object, but I kind of just fluked it, and now I realise what went wrong.

This student's reflection illustrates a strong ME-Actions or strategies connection by demonstrating the tutorial experience and understanding strategies or actions that needed to be taken to perform the task. Looking at the weight of the network connections for the ***IT-04 cohort***, low-score students had a more pronounced connection in MK-ME, similar to IT-01 and IT-02, suggesting an alignment between knowledge of their cognition and experiences during performing tasks. This indicates that while low-score students demonstrated a comprehensive knowledge of their cognition and experiences, these did not necessarily reflect in their academic performance. For example, one low-score student from the ***IT-04 cohort*** reflected:

> For the OLTP and OLAP Queries exercise using Excel, I am quite confident with my work since I've already had experience with Excel before. So I can finish the exercise quite fast. The part I enjoy the most is creating a Pivot table, where I can play around with data and revise how to use Excel in general…Even though it is a short exercise, I think it is enough for me to have an idea of how the OLTP&OLAP Queries should be performed.

This particular student reflected on knowledge and experience from prior learning and implemented that to perform a task while understanding the essential requirements to perform this task. In contrast, high-score students from this cohort (***IT-04***) demonstrated slightly lower MK-ME connections; however, they had close weighted connections in MK-Action or strategies and ME-Action or strategies. For example, one high-score student reflected:

> My role in today's learning process was to attempt to answer the second question from this week's tutorial questions. I attempted to understand and answer the question to the best of my ability by browsing various online articles. I skimmed through the articles, then interpreted the information provided in them and provided my own understanding and opinion from the information I gathered. I referenced the articles I read to validate the answer I provided, and

> I also gave examples to support my answer. I shared a rewarding collaborative process with one of my group mates. After that, we presented our work to the rest of the group, asked for feedback and suggestions, listened to others' work, and provided our take on their work.

This student reflected on knowledge of the content, strategies performed to complete the task, and shared experience of the learning session. While low-score students from this course (IT-04) reflected more on their metacognitive knowledge and experiences, high-score students applied this knowledge to experiences and actionable strategies.

Integrating the insights (from above) retrieved from the discussions across all three subjects (IT-01, IT-02, and IT-04) illustrates a multi-faceted distribution of metacognitive phenomena between high and low-score students even though the main area of these subjects was "IT". High-score students from IT-01 and IT-02 consecutively demonstrated the strongest connections in MK-ME and ME-Actions or strategies. For IT-04, MK-ME was most pronounced; MK-Actions or strategies and ME-Actions or strategies showed nearly comparable weights. Looking at the patterns of these connections, ME was common in high-score students across all three subjects. The consistency of the presence of strong ME in high performers across all subjects highlights reflective learning practices. This finding is consistent with Efklides's (2006) study on metacognition, where feelings of knowing and judgement of learning (both comprised of ME) were highlighted to be critical factors for effective learning and problem-solving. Efklides and Tsiora (2002), in their earlier paper, demonstrated that metacognitive experiences influence learners' self-concept and self-regulation in their respective academic domains. This does not suggest any definitive claim that reflecting on metacognitive experiences causes high performance but suggests ME have a complex relationship between self-awareness, regulation, and academic achievement. A study by Özcan (2016) also found that metacognitive experiences contribute to mathematical problem-solving skills. However, the connection between ME and actions or (strategies) was also common among high-score students from the IT-02 and IT-04 cohorts. This aligns with the findings by Wu et al. (2020), where "actions" had a stronger connection among high performers. Pintrich and De Groot (1990) also reported that in an English study, metacognitive strategies were positively related to performance. This may suggest that high-score learners translate metacognitive experiences into actionable strategies that are reflected in their academic performance.

Low-score learners, on the other hand, from IT-01, IT-02, and IT-04 demonstrated the strongest connection in MK-ME, suggesting low performers engage in reflecting on their learning experiences and having an awareness of their cognitive processes but are not being translated to their performance. Wu et al.'s (2020) findings support this result, where their experiment suggested that low-score students have a stronger connection with MK. However, this finding does not align with Artz and Armour-Thomas's (1992) findings on grade school learners, indicating metacognitive knowledge to be related to improved performance. Tarricone's (2011) theory of metacognitive knowledge also suggested that metacognitive knowledge is about beliefs and understanding of different aspects that influence the approach towards problems and outcomes of tasks. Although Schraw (1994) mentioned that regulatory components of metacognition occur only when metacognitive knowledge is high, on the other hand, a higher knowledge of cognition does not assure a high capability of regulation of cognition. From this point of view, low-score students across three IT courses are reflecting on their experiences and understanding of their cognitive processes but are unable to transfer this into the regulatory components of metacognition, thus creating a gap between possessing the knowledge of cognition and applying effectively in an academic context.

However, even though there are similarities in the pattern of metacognitive process between high and low performers across three IT subjects, there are several differences to note based on their levels of study and study discipline. For example, IT-01 and IT-04 had similar subject designs and focus (business and IT-related content, see section 3.3), but we see different network connections, which could be a result of different levels of study (IT-01 was an undergraduate subject, and IT-04 was a postgraduate subject). IT-01 had a stronger connection in MK-ME for high-score students; conversely, in IT-04, while the strongest connection was in MK-ME, there were also close weighted connections in ME-Actions or strategies and MK-Actions or strategies. This could be a result of older learners progressing in their studies, demonstrating a stronger link between knowledge of their cognitive processes and regulation. Schraw (1994) pointed out that older learners have a similar understanding of their learning processes compared to younger learners but differ in implementing that understanding into the regulatory components of metacognition. A study by Young and Fry (2008), using the metacognitive awareness inventory, found that older learners scored higher on regulatory components of metacognition and had no difference in knowledge of cognition, which aligns with this study's findings. Building on these insights, Urban and Urban (2021) reported that learners from preschool to university, individuals accurately assessed their capabilities over time.

Alternatively, students from IT-02 demonstrated the strongest connection in ME-Actions (or strategies) – in high-score students and MK-ME in low-score students. The difference in the pattern could be due to (1) the level of study (undergraduate students) and (2) the subject content that was based on the fundamentals of programming (introductory programming subject). Demonstration of metacognitive behaviour can vary from discipline to discipline (Aghababyan et al., 2017; Wu et al., 2020). While not entirely, the pattern in students from IT-02 aligned with Bergin et al.'s (2005) findings, suggesting that well-score learners from an introductory programming subject implemented more metacognitive strategies, where metacognitive strategies were comprised of planning, monitoring, and regulating the strategies (planning and regulating strategies fall under Actions or strategies metacognitive components of this study – see Table 7). However, a study by Eteläpelto (1993) highlighted that novice programmers possessed less metacognitive knowledge compared to expert programmers. This may suggest that while novice high-score programmers are using more regulatory aspects of metacognition and having academic achievements, this gap of not having knowledge of their cognitive processes may not lead to success as advanced programmers. Meanwhile, the pronounced connection in MK-ME in low-score learners from the same cohort suggests that these learners are more aware of their cognitive processes but failed to apply this knowledge in effective learning strategies for better outcomes. These discrepancies could be due to a lack of overall metacognitive awareness in novice programming students, which was demonstrated to be effective in supporting novice programming learners (Prather et al., 2019; Prather et al., 2018).

In addition, as highlighted earlier in this section, no significant differences were found in IT students' self-reported metacognitive awareness between these two groups across three subjects (IT-01, IT-02, and IT-04). This finding is inconsistent with previous works suggesting metacognitive awareness to have an effect on learners' academic performance (Coutinho, 2007; Hermita & Thamrin, 2015; Pintrich & De Groot, 1990; Romainville, 1994; Schleifer & Dull, 2009). Alternatively, studies also reported weak associations between metacognition and academic performance (Gul & Shehzad, 2012; Meijer et al., 2012; Ohtani & Hisasaka, 2018). However, older (IT-04) high-score had more metacognitive awareness in procedural knowledge and planning, while younger (IT-01) high performers self-reported to have higher awareness in declarative knowledge, conditional knowledge, and debugging. Low-score older learners (IT-04), on the other hand, reported higher awareness of declarative knowledge, conditional knowledge, information management, monitoring, debugging, and evaluation. Low-score younger learners (IT-01) had higher awareness of procedural knowledge, planning, information management, and monitoring. This suggests that high and low performers from IT-01 and IT-04 did not demonstrate any specific patterns in their self-reported metacognitive awareness, even though both of these subjects followed a similar structure (highlighted earlier), where the differences were in – (1) level of study and (2) a significant proportion of students from IT-04 were international students. Age differences contribute to changes in the implementation of metacognition (Filippi et al., 2020; McGillivray & Castel, 2017; Schraw, 1994; Urban & Urban, 2021; Young & Fry, 2008). Additionally, as the IT-04 cohort had a significant number of international students, this may have contributed to the absence of patterns between high and low-score students from IT-01 and IT-04 in their metacognitive awareness. This aligns with the findings of Lewthwaite (1996) and Smith and Khawaja (2011), who stressed that the adjustments to new educational environments could catalyse specific metacognitive strategies as international learners go through challenges in adapting to different environments and academic settings, which may lead to frustration and depression. However, metacognitive components may be acquired from teachers, peers, and learners' cultures, which are all interrelated in metacognitive theories (Schraw & Moshman, 1995).

Tying the knots, while initial theories, based on substantial previous research, suggested a positive relationship between students' metacognition and academic performance, findings from this research rather suggest a more nuanced and complex nature of the association. Through the analysis and findings of the metacognitive (processes) in high and low-score students across three subjects challenge the straightforward association of metacognitive components with academic performance. It is also essential to note the different metacognition (processes) high and low-score students demonstrate even though all three subjects were from the same discipline (IT) with a different subject-learning focus. This suggests that demonstration of metacognition varies not only with students' disciplines but also with their subject-learning focus. Furthermore, previous studies suggested that metacognition alone may not be a predictor of academic achievement. A study by Kelly and Donaldson (2016) reported that metacognition, along with learners' high consciousness, can only be a good predictor of academic success. Additionally, they have mentioned that metacognition and learners' personalities play an important role in academic success, which is often not considered. Implementing MASEM (metaSEM package in R), Ohtani and Hisasaka (2018) reported that metacognition with intelligence is a successful predictor of academic performance. In addition, the probable effect of students' study level and students' culture on their metacognitive (processes) was also highlighted. These combined discussions suggest a revaluation of the direct relationship between metacognition and academic success, while metacognition can be influenced by other factors illustrating a multifaced nature.

5.2 Differences in Metacognition Between IT Students with and without Intervention

Research question 2 addressed the differences between the metacognition of IT students who experienced the intervention and those who did not. From Figure 19 and Figure 20, it was observed that both groups (students who received metacognitive interventions and those who did not) self-reported an increased metacognitive awareness at the end of the semester, demonstrating a greater balance in knowledge of cognition and regulation of cognition. However, no significant differences between these two groups of students in their pre and post-MAI scores were found.

Even though the differences are not significant, it is important to have a granular understanding of the sub-components of these self-reported pre and post-MAI scores. From Table 17 and Table 18, it was found that students who experienced metacognitive interventions (IT-04) demonstrated increased awareness (although not significantly different) of declarative knowledge, procedural knowledge, and planning at the end of the semester. Students who did not receive the interventions (IT-05), on the other hand, demonstrated increased awareness of conditional knowledge information management, monitoring, debugging, and evaluation. This suggests that students who received the interventions demonstrated a higher increase in knowledge of cognition (declarative and procedural), and students who did not receive any interventions demonstrated a higher increase of metacognitive awareness in the regulation of cognition (information management, monitoring, debugging, and evaluation). Some studies have found increased metacognitive awareness after implementing interventions. For example, a study by Doyle (2013), where metacognitive awareness was measured using the metacognitive awareness inventory (MAI), and reflection as writing was implemented as one of the metacognitive interventions in pre-nursing students. They reported that students' knowledge of cognition significantly increased after metacognitive interventions; however, no significant increase was reported in the regulation of cognition. Similarly, in another study by Rivas et al. (2022) on first-year psychology students, promoting reflection with review, correction, and clarification in a group and aiming for students to be conscious of their own thinking processes, they reported that after interventions, students demonstrated a higher increase in declarative knowledge, procedural knowledge, conditional knowledge, planning, and monitoring. Albeit not entirely, this result aligns with the findings of this research that metacognitive interventions increased declarative, procedural, and planning aspects of metacognitive awareness. Amzil (2014) also implemented metacognitive interventions using reflective dialogue, and it was reported that metacognitive interventions increased college students' metacognitive knowledge, monitoring, and control. Another study by Sandi-Urena (2008), where reflection was implemented as an intervention along with social interaction, highlighted that the interventions enhanced "awareness" and "use of metacognition" in tasks for chemistry problem-solving.

However, other studies did not find any significant increase in students' metacognitive awareness after intervention. For example, Dang et al. (2018), in their study implementing reflective questions in assignments and using the metacognitive awareness inventory (MAI), reported that there was no significant difference in students' MAI scores from the beginning to the end of the semester in an introductory biology course; this aligns with the result retrieved from this study. Similar to this finding, Soicher and Gurung (2017) implementing exam wrappers as an intervention did not cause an increase in students' MAI scores. However, from this study, both groups of students who experienced intervention and those who did not have increased metacognitive awareness at the end of the semester, which aligns with Thompson's (2012) study, while Soicher and Gurung (2017) argued that this increase may only be a result of the "maturation effect" as learners progress in their learning (maturing from the beginning of the semester to the end).

Several differences were also observed in the temporal patterns in students' learning traces between students who experienced metacognitive interventions (IT-04) and students who did not receive the intervention (IT-05). For example, it was found that during the weekly tutorials, students who experienced higher metacognition performed actions that focused on planning (Subject Outline View and Subject Announcement View) and evaluation (Subject Grade View) before viewing weekly tutorial content. This suggests that students from this cohort took measures to understand the outline of the subject (planning), stay informed about the subject announcements (planning), and evaluate their performance (Subject Grade View) before proceeding with viewing the weekly tutorial content, suggesting a proactive approach. However, no absolute frequency was observed before "Weekly Tutorial Content View" among students who did not receive the interventions. This indicates that students who did not receive the interventions were less likely to plan and evaluate their learning before starting a learning session.

Additionally, students who received the intervention demonstrated a presence of the "monitoring" component in their absolute learning traces in two observations, unlike students who did not experience the intervention. Firstly, starting from viewing the list of subject assignments (List of Subject Assignments View – Planning) to submitting the subject assignments (Subject Assignments Participation – Completing a task), students who experienced the intervention implemented most of the regulatory components of metacognition (information management, monitoring, and evaluation). Although this does not align with the ideal sequence of planning before the task, information management and monitoring during the task and evaluation after performing the task (Pintrich, 2004), it highlights the presence of these components. It also reflects a more nuanced understanding of students regulating their learning, suggesting the key to enhanced performance may lie more in the ability to apply the regulatory components (Zimmerman, 2002). However, students who did not receive the interventions, starting from viewing the list of subject assignments (List of Subject Assignments View – Planning) to submitting the subject assignments (Subject Assignments Participation – Completing a task), demonstrated only planning, information management, and evaluation components of regulation of cognition. These traces highlight the absence of "monitoring" in students who did not receive the intervention. This finding aligns with the study of Mevarech and Amrany (2008), indicating that metacognitive interventions increased regulatory components of metacognition. The absence of the "monitoring" component of the regulation of cognition in students who did not receive the intervention suggests a gap in their ability to assess and adjust their understanding or learning strategies.

Secondly, students who received interventions demonstrated both direct and indirect absolute frequency paths towards "Monitoring", while students who did not receive the interventions did not demonstrate any direct or indirect path towards "Monitoring". This indicates that students who received the interventions effectively implemented continuous assessment of their learning, which was not reflected in the learning traces of students who did not receive metacognitive interventions. Monitoring in regulation is an integral part of metacognition (J. H. Flavell, 1979) that has been analysed and reported to be an effective and important aspect of learning (Desoete, 2008; Hertzog & Dunlosky, 2011; Lingel et al., 2019). The components of the regulation of cognition are also highly interdependent (Veenman et al., 2004). Thus, the absence of the "monitoring" component among students who did not experience the metacognitive interventions suggests they might be missing this critical component of metacognition (Schraw, 1998). Englert et al. (1988) also reported that high performers, compared to low performers, implemented more monitoring strategies, which suggests the need for a monitoring component for academic performance. This lack of monitoring could be due to not receiving the metacognitive interventions (metacognitive talk time and reflections), as highlighted by Schraw and Gutierrez (2015) that think aloud after a task as post-learning reflection (one of the suggested instructional metacognitive strategies for teaching monitoring) can lead to improved "monitoring". However, both of these groups of students demonstrated implementing evaluation ("Subject Grade View") before completing a task and demonstrating calibration.

From the activity statistics demonstrated in section 4.2.2.2, it was observed that students who received metacognitive interventions demonstrated a gradual decrease in their implementation of metacognition while relatively focusing highly on information management, planning, and evaluation, then completing tasks and least implementation of “monitoring”. However, students who did not receive the intervention demonstrated a steep decline from planning to completing a task, focusing significantly more on information management and planning. This implies that students who received metacognitive interventions demonstrated a more balanced approach (smoothness in decline) compared to those who did not (steep decline). The uniform decline in the regulatory components of metacognition within students who received the interventions suggests that these students applied a variety of regulatory components of metacognition throughout the learning process, while students who did not receive interventions were only highly focused on information management and planning. This indicates a more comprehensive use of regulatory aspects of metacognition within students receiving interventions. Additionally, students who received metacognitive interventions demonstrated a gradual engagement with various learning contents, while students who did not receive the intervention highly focused on only “Weekly Prepare Resource – Information Management” and “Attachment View – Information Management” learning components. This points out that while students who experienced intervention engaged with diverse learning content implementing various components of regulation of cognition, students who did not receive intervention exhibited a limited approach in implementing regulatory components of metacognition to learning. Thomas and McRobbie (2001) and Sandi-Urena et al. (2011) in their study reported that intervention enhanced the metacognitive skills and learning processes of students in chemistry lessons. Moreover, Schraw et al. (2012) reported that after metacognitive intervention, an improvement in knowledge and regulation of cognition was observed in fifth-grade students. This limited implementation of regulatory components of metacognition could be due to students not receiving the metacognitive intervention, thus being unable to apply the regulative components of metacognition. Promoting metacognition is essential (Schraw, 2001). Furthermore, Veenman (2017) highlighted the necessity of embedding metacognitive instructions and informing learners about the importance of metacognition; both of these were implemented as a part of the metacognitive intervention in this study. The necessity highlighted re-affirms this study’s finding, indicating that students who experienced metacognitive intervention exhibited diverse engagement with the regulatory components, while limited use of the regulatory components was observed in students who did not receive the intervention.

In summary, IT students who received metacognitive interventions demonstrated a higher increase in only declarative knowledge, procedural knowledge, and monitoring, while students who did not receive any intervention reported increased metacognitive awareness in conditional knowledge, information management, monitoring, debugging, and evaluation. However, students who received intervention demonstrated higher interactions with the learning content compared to those who did not experience the intervention. In contrast, students who received the intervention demonstrated higher interaction with the regulative components of metacognition (with a presence of monitoring in their absolute learning traces). These suggest that, for students who demonstrated higher regulation of cognition in their learning traces, their metacognitive awareness scores did not reflect this. This finding contradicts the results of other studies. For example, Akcaoğlu et al. (2023) found that awareness has an effect on regulation. It also contradicts the study of Pressley and Ghatala (1990; as cited in Schraw & Dennison, 1994), where it was highlighted that metacognitively aware learners are more strategic than unaware learners. This inconsistency suggests that being aware of one’s metacognition may not always be reflected in one's learning traces. For instance, students who did not experience the intervention had higher scores in regulatory components of metacognition, but their learning traces did not reflect this; their awareness may not be translated into implementation in the learning process. Reflecting on the learning process for metacognitive awareness, students may have experienced memory failure and distortion (Nisbett & Wilson, 1977). However, the non-significant differences in students who experienced metacognitive interventions and those who did not could be due to the duration of the intervention. Veenman (2017) highlighted the necessity of duration of instructions for executing metacognition. Soicher and Gurung (2017) also argued that students might not demonstrate significantly increased metacognition as they may lack an understanding of the benefit of metacognition and associated activities around it as it was being implemented in only one subject. Metacognition has wider capability when implemented across the curriculum rather than implemented in “isolated” sessions for better outcomes (Perry et al., 2019). Promoting metacognitive awareness can be done through reflections and metacognitive instructions (Schraw, 2001; Schraw & Gutierrez, 2015; Veenman et al., 2006).

5.3 IT Students' Associated Linguistic Features with Metacognitive Awareness and Academic Performance

Research question 3 addressed the significant linguistic features associated with metacognitive awareness and academic performance from students' written reflections. From a **metacognitive awareness** point of view, few linguistic patterns in students' reflective writing were observed from the analysis of profiles across the quartiles of metacognitive awareness scores. Lower quartile students with lower metacognitive scores (***Q1***) demonstrated an inclination towards self-focus in their reflections, emphasising less on group reflections ("we"). Reflective writings of this group of students also highlighted highly recognising discrepancies and focused on past experiences, with a low negative tone. Students in ***Q2*** demonstrated a "blended approach" in using first person singular and plural pronouns, i.e., "i" and "we", suggesting a combination of group ("we") and individual ("i") reflection while focusing on highly past experiences. This may suggest that students in this group relied on past experiences to grasp the discrepancies in their own cognitive processes. However, students in ***Q3*** (third quartile) showcased the use of three first-person singular and plural pronouns, including third-person singular pronouns ("i", "we", and "shehe"), with lower discrepancy compared to Q1 and Q2. This is consistent with the model by Gibson et al. (2016), where metacognition and reflection are a continuum. It can range from non-conscious (implicit metacognition – inner-self) to external social self (conscious social reflection). Explicit metacognition or conscious metacognition and personal reflection fall in the middle. The ***UQ*** group (upper quartile group) focused more on self-reflection ("i") and less on group reflection ("we"), demonstrating a higher negative tone and the least discrepancy in their written reflections.

This consistent use of first-person pronouns among all the MAI score quartiles aligns with the preliminary findings of Huang et al. (2019), where it was found that metacognitive phrases began with pronouns, with few exceptions. Although not demonstrating any significant pattern in the use of certitude-related words among the MAI quartiles, Efklides (2011) highlighted that this cognitive state, i.e., certainty, has an impact on metacognitive experiences. It is also important to highlight the average word count of these groups of students in their written reflections, which do not follow a distinctive pattern. This is consistent with findings from previous studies highlighting the necessity of the quality of reflections rather than focusing on their length (Gibson et al., 2016; Liu et al., 2019). Barthakur et al.'s (2022) study contradicted this finding and reported that higher-quality reflections were associated with higher word counts. Another point to note is that discrepancy-related words declined from lower to higher MAI quartiles. This finding does not support Pennebaker's (2011) study suggesting that higher discrepancy-related words would indicate higher analytical thinking. Although the observed profiles do not indicate any specific linguistic pattern use, it is essential to understand the insights it is providing into the reflective processes and metacognitive awareness.

From a subject **performance (final score)** view, high achieving students (***Q3*** and ***UQ***) were inclined more to use self-reflective ("i") and group reflective ("we") words, indicating a mixture of using first-person singular and plural pronouns. The use of these pronouns was further expressed in positive emotion and a stronger tendency to reflect on past experiences more than focusing completely on the present. Interestingly, these students also used a higher amount of words in their written reflections, which suggests an extensive examination of their experiences and thoughts. This approach of relying on and leveraging past experiences and reflecting on discrepancies with a highly positive tone indicated a constructive approach for high performers in their learning. Alternatively, lower-score students (***Q1*** and ***Q2***) demonstrated a contrast pattern in their linguistic features. Students from this group emphasised highly on self-reflection ("i") and moderate use of group-focused ("we") words in their reflections, using fewer words compared to their higher performing (Q3 and UQ) peers. This finding is consistent with the results of Abe's (2020) study, where an association between word count and academic achievement was reported. Remarkably, no observable pattern in discrepancy-related words was found among the quartiles from the final score. This finding is inconsistent with Rodrigo's (2017; as cited in Peterson et al., 2018) study, where a positive correlation between level of discrepancy and academic performance was reported. However, this study employed overall subject performance, whereas Rodrigo's study focused on reflective writing scores.

Taken together, these findings underscore the complicated and multi-faceted connection among linguistic features, metacognitive abilities, and academic performance. However, combining both academic performance and metacognitive awareness, certain linguistic features demonstrated to have an association with both of these aspects, such as first-person singular and plural pronouns ("i" and "we"), discrepancy, and focus on the past. It is also essential to understand that even though these features are shared in both metacognitive awareness and academic performance, individually, they may not share an identical profile. This suggests a need for further research to refine the understanding of the contribution of linguistic features to metacognitive awareness and academic performance.

5.4 Implications

Metacognition is an essential part of learning. Based on the findings and discussion outlined in the earlier sections, several key implications emerge, particularly in the field of IT education, for pedagogical practice, educational administrators, and researchers. The following subsections discuss each implication.

5.4.1 Implications for Pedagogical Practice

Teachers should understand the importance of metacognition and integrate that into their teaching strategies to help students improve their awareness of their own learning process. This may include incorporating reflective writing activities, self-assessment throughout the learning, and tailored interventions. Additionally, using learning data and different learning analysis methods, teachers can get significant insights into students' metacognition and who may benefit from extra support to improve their metacognitive skills. For example, by understanding the differences in high and low-score IT students' metacognitive processes, teachers can identify the gaps in low-score students' learning and provide targeted interventions. This targeted approach ensures that all students are benefiting from the "metacognitive" practices in learning. Moreover, as highlighted earlier, it is essential to empower students to understand and recognise the importance of metacognition. By embedding metacognition in the curriculum, teachers can foster critical and creative thinking and self-regulation skills that are essential for 21st-century skills.

5.4.2 Implications for Educational Administrators

Educational administrators can play a crucial role in fostering an environment that can support the development of metacognition. By implementing professional development programs, educational administrators can equip teachers with the necessary skills and knowledge to incorporate "metacognition" into their teaching strategies. As Prytula (2012) highlighted, a professional learning community nurtures teachers' metacognition, which can be facilitated by administrators. These programs should include training on using different learning analytics methods to gain effective insights into students' metacognition, understanding how different disciplines' students' metacognition differs, and how to incorporate metacognitive intervention into students' learning. As highlighted in the earlier sections above, metacognition has a greater impact when implemented across the curriculum rather than in an "isolated" session. Additionally, it is important for the teachers to guide the students in recognising the significance of metacognition in learning. Thus, creating an environment for teachers to nurture and gain skills to foster students' development of metacognition is essential. In addition, as stressed by Azevedo (2020), educational administrators need to develop and customise their system in a way that ensures ethical standards and reduces the possibility of inconsistent and missing data. Moreover, administrators should also consider dedicating resources to research on understanding students' metacognition that can further improve institutions' education practices and cultivate lifelong learning in students.

5.4.3 Implications for Researchers

The findings of this study offer significant implications for studies in the area of IT education. Leveraging insights from this study, researchers can develop more effective analysis approaches to understand the nuances of IT students' metacognition and design more effective targeted support methods for developing students' metacognition. Additionally, researchers can also apply the effective learning analytics approaches implemented in this study, i.e., epistemic network analysis, process mining, and linguistic inquiry approach, to other IT subjects within different educational contexts. This can help in identifying specific patterns and effective interventions that can influence IT students' metacognition more efficiently. Combining techniques from different interdisciplinary resources, such as educational psychology, data science, and learning analytics, as implemented in this study, researchers can develop innovative tools and strategies that can be applied widely. Furthermore, researchers can use the frameworks implemented in this study to evaluate and understand metacognition across diverse student populations in different educational contexts. The continuous adaptation and refinement of these frameworks will contribute towards advancing educational practices, ensuring effective learning with metacognition in IT education and beyond. Possible future works emerging from this research are outlined in the following section (see section 6.2).

Chapter 6

Conclusion, Limitations, and Future Work

This chapter provides concluding remarks by outlining the key findings and contributions of our research (section 6.1), highlighting the limitations of this study (section 6.2), and suggesting future works that can be expanded from our findings (section 6.3).

6.1 Conclusion

This study significantly contributes to the existing literature by exploring IT students' metacognition, implementing learning analytics approaches, and using a theoretical lens to analyse and understand the data, i.e., written reflections, learning traces, final scores, and metacognitive awareness scores. By implementing different analysis methods (e.g., epistemic network analysis, process mining, and linguistic word count approach), this research uncovers significant insights into IT students' metacognition in a higher education context that can be embedded into the pedagogical strategies.

One of the key contributions of this study was the identification of the noteworthy differences between high and low-score IT students' metacognitive (processes) across different subjects and levels of study. Additionally, this study also contributes to our understanding of significant linguistic features that were associated with IT students' academic performance and metacognitive awareness. These contribute to the existing studies by exploring the domain of IT education and providing significant insights into reflections and (1) their patterns in high and low-score students and (2) their complex association with metacognitive awareness and academic performance. Moreover, the process mining technique allowed us to understand differences in IT students' learning traces between those who experienced the intervention and those who did not. Understanding the significance of metacognitive intervention, along with its impact on students' learning processes, adds value to existing knowledge of metacognition and its importance in incorporating it into the teaching practice. Contributions of this study equip teachers and educational organisations with crucial knowledge to enhance teaching practices in IT education. Overall, this research contributed to the field, offering theoretical and practical implications for understanding and improving IT students' metacognition.

6.2 Limitations and Future Work

Nevertheless, it is important to recognise and acknowledge the limitations of this study. With a limited sample size and participants restricted to a few IT subjects, the extent to which generalisations can be made regarding the analysis of students' metacognition is somewhat limited. Additionally, analysis was performed based on the data collected at an Australian university. Thus, demographical differences may or may not influence the results of the analysis. However, several possible future strands of research can be identified from this study.

- Future research studies should expand the sample size and strive to incorporate students' data from various IT subjects across educational contexts. Expanding the work will improve this study's credibility and provide a more nuanced understanding of IT students' metacognition.
- Additionally, future studies can analyse the long-term effects of interventions on IT students.
- Moreover, implementing the intervention across subjects of students' study will allow us to have deeper insights into how students' metacognition changes when implemented widely.
- On top of these, examining the influence of cultural differences in influencing IT students' metacognition could provide a more comprehensive understanding of the effect of diverse cultural backgrounds on shaping IT students' metacognition.
- Lastly, future studies could explore this area by implementing more advanced analysis techniques to gain deeper insights into the complex interactions between the metacognitive components, thereby making a contribution toward tailored support strategies.

By exploring these directions, we will be able to enhance our understanding of metacognition further and develop more efficient pedagogical approaches tailored to IT students to support their learning and development.

Appendices

A. Research Data Management Plan

The research data management plan was created within the institution’s research data management systems (Stash). The following figures in this section contain an illustration of the research data management plan of this study (see Appendix Figure 1). The sequence of snapshots of the document flows from left to right.

Appendix Figure 1: Research Data Management Plan

Page 1 of the Research Data Management Plan	Page 2 of the Research Data Management Plan
UTS Stash **From Data to Insight: Understanding Students’ Metacognition Through Learning Analytics Using Written Reflections and Learning Traces** **Description** Metacognition is a multi-faceted skill that allows students to develop their learning processes effectively. Although metacognition has been studied for decades, there are still limitations to the existing literature in understanding how students employ metacognition in their studies. Understanding students’ implementation of metacognition using contemporary epistemic network analysis, process mining, and natural language processing techniques bridges the gaps and adds value to the existing pedagogical practices. In this study, we aimed to understand students’ metacognitive (processes) through their written reflections and learning traces. We have examined the high and low-score students’ metacognitive processes from students’ reflective writing and self-reported metacognitive awareness scores using epistemic network analysis. Additionally, we analysed the differences in students’ learning traces when metacognitive interventions were applied using the process mining technique. Lastly, we examined the linguistic features that had significant associations with students’ self-reported metacognitive awareness and their academic performance using the Linguistic Inquiry Word Count Approach. Data was collected during two semesters from students enrolled in undergraduate and postgraduate subjects at the Faculty of Engineering and Information Technology at the University of Technology Sydney. The results indicated that there was no significant difference between high and low-score students’ implementation of metacognition in their written reflections and self-reported metacognitive awareness. However, differences in the distribution of metacognitive phenomena were observed among cohorts from different subjects and their levels of study. Additionally, results indicated that learning traces and engagement with the learning content varied between students of the cohort who experienced the metacognitive intervention and those who did not. Students who received intervention demonstrated varied interaction with the learning content with a higher presence of regulatory components of metacognition. On the contrary, students who did not receive the intervention demonstrated limited interaction with the subject content and regulatory aspects of metacognition. The final result from this study showed how certain linguistic features, e.g., personal pronoun, time orientation, tone, emotion, and discrepancy, were significantly associated with students’ self-reported metacognitive awareness and their academic performance. This research contributes to developing our existing knowledge of metacognition in educational practices and highlights the importance of incorporating metacognition into subject design. Expand/Collapse all	**- Project** **Project overview** **Project name** From Data to Insight: Understanding Students’ Metacognition Through Learning Analytics Using Written Reflections and Learning Traces **Research Master Project Code / Student ID** 24544520 **HDR student project** **Project description** Metacognition is a multi-faceted skill that allows students to develop their learning processes effectively. Although metacognition has been studied for decades, there are still limitations to the existing literature in understanding how students employ metacognition in their studies. Understanding students’ implementation of metacognition using contemporary epistemic network analysis, process mining, and natural language processing techniques bridges the gaps and adds value to the existing pedagogical practices. In this study, we aimed to understand students’ metacognitive (processes) through their written reflections and learning traces. We have examined the high and low-score students’ metacognitive processes from students’ reflective writing and self-reported metacognitive awareness scores using epistemic network analysis. Additionally, we analysed the differences in students’ learning traces when metacognitive interventions were applied using the process mining technique. Lastly, we examined the linguistic features that had significant associations with students’ self-reported metacognitive awareness and their academic performance using the Linguistic Inquiry Word Count Approach. Data was collected during two semesters from students enrolled in undergraduate and postgraduate subjects at the Faculty of Engineering and Information Technology at the University of Technology Sydney. The results indicated that there was no significant difference between high and low-score students’ implementation of metacognition in their written reflections and self-reported metacognitive awareness. However, differences in the distribution of metacognitive phenomena were observed among cohorts from different subjects and their levels of study. Additionally, results indicated that learning traces and engagement with the learning content varied between students of the cohort who experienced the metacognitive intervention and those who did not. Students who received intervention demonstrated varied interaction with the learning content with a higher presence of regulatory components of metacognition. On the contrary, students who did not receive the intervention demonstrated limited interaction with the subject content and regulatory aspects of metacognition. The final result from this study showed how certain linguistic features, e.g., personal pronoun, time orientation, tone, emotion, and discrepancy, were significantly associated with students’ self-reported metacognitive awareness and their academic performance. This research contributes to developing our existing knowledge of metacognition in educational practices and highlights the importance of incorporating metacognition into subject design. **Keywords** Metacognition, Learning Analytics, Reflection, Learning traces, Information Technology, Epistemic Network Analysis, Process Mining, Natural Language Processing, LIWC **Start date** 01/07/2022 **End date**

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30/06/2024

Funders

Grant ID

- People

People

First-named chief investigator / UTS supervisor

Name	Email	Project Role	ORCID
Amara Atif	Amara.Atif@uts.edu.au	Chief Investigator	

Data manager

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Contributors

Name	Email	ORCID

Additional supervisors

Name	Email	ORCID
Lisa-Angelique Lim	Lisa-Angelique.Lim@uts.edu.au	

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- Ethics and security

Ethics and Security

Initially your research data is classifed as UTS Internal. To improve the accuracy of this classification, please answer the following

Information Security Classification
UTS: Confidential

Does the research involve:
Human participant data

Will the data you collect from individuals include personal information?
No

Will the data you collect from individuals include sensitive personal information other than health information?
No

Will the data you collect from individuals include health information?
No

Will any data or information be individually identifiable or potentially re-identifiable (i.e. include codes) at any stage of the research?
No

Is Ethics approval required for your project?
Yes

- Data collection and storage

Data collection and storage

Please provide a brief description of your data collection methodology
Both quantitative and qualitative data from Qualtrics survey and Canvas learning management systems

Predominant file type(s), e.g. textual, tabular, image or recording. Give file format if known
Numerical and textual data. Predominant file types is: Excel

Data storage location
Shared university network drive (e.g. G, H, etc)
UTS provided survey platform (e.g Qualtrics, REDCap, etc)
UTS provided collaboration space (e.g. CloudStor, OneDrive etc)

If other, provide further details: (Including access arrangements for the minimum retention period)

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- Data retention and disposal

Data retention and disposal

Minimum retention period
5 years (general research)

The data steward is:
Amara Atif

Have you made commitments to destroy part of the data prior to end of retention period (e.g original recordings, linking/code files)?
No

When should it be destroyed?
31/12/2027

- Access and rights

Access and rights

Copyright and intellectual property owners of data created in project
Higher Degree Research Student

Please list any other owners:
Amara Atif & Lisa-Angelique Lim

Access after the project will be
Mediated, by permission from the data manager

Are you using any secondary or third-party data?
No

Licences or Agreements:

B. Ethics Approval

The ethics application for this study was submitted to the UTS Ethics Approval Committee before proceeding with the data collection on 20 January 2023. Approval of the ethics application was received via email on 14 February 2023. Appendix Figure 2 contain snapshots of the email received for ethics approval.

Appendix Figure 2: Ethics Approval Notification

Page 1 of the Ethics Approval Notification	Page 2 of the Ethics Approval Notification
Your ethics application has been approved as low risk - ETH23-7893 research.ethics@uts.edu.au <research.ethics@uts.edu.au> Tue 14/02/2023 7:23 PM To:Amara Atif <Amara.Atif@uts.edu.au>;Maliha Homaira <Maliha.Homaira@student.uts.edu.au> Cc:Research Ethics <research.ethics@uts.edu.au> 1 attachments (365 KB) Ethics Application.pdf; Dear Applicant, **Re: ETH23-7893 - "Metacognition with learning analytics"** Your local research office has reviewed your application and agreed that it now meets the requirements of the National Statement on Ethical Conduct in Human Research (2007) and has been approved on that basis. You are therefore authorised to commence activities as outlined in your application, subject to any conditions detailed in this document. You are reminded that this letter constitutes ethics approval only. This research project must also be undertaken in accordance with all UTS policies and guidelines including the Research Management Policy. Your approval number is UTS HREC REF NO. ETH23-7893 Approval will be for a period of five (5) years from the date of this correspondence subject to the submission of annual progress reports. The following standard conditions apply to your approval: • Your approval number must be included in all participant material and advertisements. Any advertisements on Staff Connect without an approval number will be removed. • The Principal Investigator will immediately report anything that might warrant review of ethical approval of the project to the Ethics Secretariat. • The Principal Investigator will notify the Committee of any event that requires a modification to the protocol or other project documents, and submit any required amendments prior to implementation. Instructions on how to submit an amendment application can be found here.	• The Principal Investigator will report to the UTS HREC or UTS MREC annually and notify the Committee when the project is completed at all sites. The Principal Investigator will notify the Committee of any plan to extend the duration of the project past the approval period listed above. • The Principal Investigator will obtain any additional approvals or authorisations as required (e.g. from other ethics committees, collaborating institutions, supporting organisations). • The Principal Investigator will notify the Committee of his or her inability to continue as Principal Investigator including the name of and contact information for a replacement. This research must be undertaken in compliance with the Australian Code for the Responsible Conduct of Research and National Statement on Ethical Conduct in Human Research. ://outlook.office.com/mail/id/AAQkAGMyZDAwZjk3LTc3MTItNDM0Yi1hMDY4LWRkYmM3MDk1ZWI4MAAQACUXytCUFwxJgCTryUpv%2FC... !4, 2:14 PM Mail - Maliha Homaira - Outlook You should consider this your official letter of approval. If you have any queries about this approval, or require any amendments to your approval in future, please do not hesitate to contact your local research office or the Ethics Secretariat. --------------------------------------- Ref: 12a

C. Consent Form

Metacognition with Learning Analytics

You are invited to participate in a study to assist researchers in analysing and comprehending how students use metacognitive techniques. Completing this survey allows you to reflect on your learning approaches and measure your metacognitive awareness level. It will provide insights into your metacognitive awareness and identify areas for improvement. When filling out the Metacognitive Awareness Inventory (MAI) survey, it is essential to approach the questions thoughtfully and honestly.

You should reflect on your learning habits and strategies as you answer the questions. Consider how you approach new learning tasks, monitor your progress, and evaluate your learning outcomes. It is also essential to remember that there are no right or wrong answers to the MAI survey. The purpose of the study is to measure your metacognitive awareness, not to judge your learning abilities. Guessing or providing answers that you think are expected from you is highly discouraged; instead, provide responses that reflect your learning process.

If you decide to participate, you will be asked to complete a survey that will take around 10 minutes of your time.

Please complete the questions below, either by writing your answer or ticking the appropriate option. Any confidential information pertaining to individuals will not be released to anybody outside the research team. Only the aggregated results will be presented and/or published. Any information or personal details gathered in the course of the research are confidential. No individual will be identified in any publication of the results. Only the researchers listed above will have access to the data.

Participation in this study is voluntary: you are not obliged to participate. If you decide to participate, you are free to withdraw at any time without giving a reason and without consequence.

Ms Maliha Homaira (**maliha.homaira@student.uts.edu.au**) is conducting the study to meet the requirements for the degree of Masters of Analytics (Research). The UTS Human Research Ethics Committee has approved the ethical aspects of this study (**ETH23-7893**). If you have any questions about this study, please contact the supervisors, Amara Atif, at **amara.atif@uts.edu.au** or Lisa-Angelique Lim, at **lisa-angelique.lim@uts.edu.au**).

Consent Statement

Let's get started!

I don't want to participate

D. Pre-MAI Survey

The Metacognitive Awareness Inventory (MAI) was disseminated to the students at the beginning and end of the semesters. The following snippets represent the MAI delivered at the beginning of the semester (Pre-MAI).

Appendix Figure 3: Pre-MAI Survey Question (1-13)

The Metacognitive Awareness Inventory

(Please rate the following statements based on how often you do each of the following activities. Select the option that best describes how frequently you engage in the activity described in each statement)

	I "never" do this	I do this "infrequently"	I do this "inconsistently"	I do this "frequently"	I do this "always"
1. I ask myself periodically if I am meeting my goals.	○	○	○	○	○
2. I consider several alternatives to a problem before I answer.	○	○	○	○	○
3. I try to use strategies that have worked in the past.	○	○	○	○	○
4. I pace myself while learning in order to have enough time.	○	○	○	○	○
5. I understand my intellectual strengths and weaknesses.	○	○	○	○	○
6. I think about what I really need to learn before I begin a task.	○	○	○	○	○
7. I know how well I did once I finish a test.	○	○	○	○	○
8. I set specific goals before I begin a task.	○	○	○	○	○
9. I slow down when I encounter important information.	○	○	○	○	○
10. I know what kind of information is most important to learn.	○	○	○	○	○
11. I ask myself if I have considered all options when solving a problem.	○	○	○	○	○
12. I am good at organising information.	○	○	○	○	○
13. I consciously focus my attention on important information.	○	○	○	○	○

Appendix Figure 4: Pre-MAI Survey Question (14-26)

14. I have a specific purpose for each strategy I use.	○	○	○	○	○
15. I learn best when I know something about the topic.	○	○	○	○	○
16. I know what the teacher expects me to learn.	○	○	○	○	○
17. I am good at remembering information.	○	○	○	○	○
18. I use different learning strategies depending on the situation.	○	○	○	○	○
19. I ask myself if there was an easier way to do things after I finish a task.	○	○	○	○	○
20. I have control over how well I learn.	○	○	○	○	○
21. I periodically review to help me understand important relationships.	○	○	○	○	○
22. I ask myself questions about the material before I begin.	○	○	○	○	○
23. I think of several ways to solve a problem and choose the best one.	○	○	○	○	○
24. I summarise what I’ve learned after I finish.	○	○	○	○	○
25. I ask others for help when I don’t understand something.	○	○	○	○	○
26. I can motivate myself to learn when I need to.	○	○	○	○	○

Appendix Figure 5: Pre-MAI Survey Question (27-39)

	I "never" do this	I do this "infrequently"	I do this "inconsistently"	I do this "frequently"	I do this "always"
27. I am aware of what strategies I use when I study.	○	○	○	○	○
28. I consider several alternatives to a problem before I answer.	○	○	○	○	○
29. I use my intellectual strengths to compensate for my weaknesses.	○	○	○	○	○
30. I focus on the meaning and significance of new information.	○	○	○	○	○
31. I create my own examples to make information more meaningful.	○	○	○	○	○
32. I am a good judge of how well I understand something.	○	○	○	○	○
33. I find myself using helpful learning strategies automatically.	○	○	○	○	○
34. I find myself pausing regularly to check my comprehension.	○	○	○	○	○
35. I know when each strategy I use will be most effective.	○	○	○	○	○
36. I ask myself how well I accomplish my goals once I'm finished.	○	○	○	○	○
37. I draw pictures or diagrams to help me understand while learning.	○	○	○	○	○
38. I ask myself if I have considered all options after I solve a problem.	○	○	○	○	○
39. I try to translate new information into my own words.	○	○	○	○	○

Appendix Figure 6: Pre-MAI Survey Question (40-52)

40. I change strategies when I fail to understand.	○	○	○	○	○
41. I use the organisational structure of the text to help me learn.	○	○	○	○	○
42. I read instructions carefully before I begin a task.	○	○	○	○	○
43. I ask myself if what I'm reading is related to what I already know.	○	○	○	○	○
44. I re -evaluate my assumptions when I get confused.	○	○	○	○	○
45. I organise my time to best accomplish my goals.	○	○	○	○	○
46. I learn more when I am interested in the topic.	○	○	○	○	○
47. I try to break studying down into smaller steps.	○	○	○	○	○
48. I focus on overall meaning rather than specifics.	○	○	○	○	○
49. I ask myself questions about how well I am doing while I'm learning something new.	○	○	○	○	○
50. I ask myself if I learned as much as I could have once I finish a task.	○	○	○	○	○
51. I stop and go back over new information that is not clear.	○	○	○	○	○
52. I stop and reread when I get confused.	○	○	○	○	○

E. Post-MAI Survey

The Metacognitive Awareness Inventory (MAI) was disseminated to the students at the beginning and end of the semesters. The following snippets represent the MAI delivered at the end of the semester (Post-MAI).

Appendix Figure 7: Post-MAI Survey Question (1-13)

The Metacognitive Awareness Inventory

(Please rate the following statements based on how often you do each of the following activities. Select the option that best describes how frequently you engage in the activity described in each statement)

	I "never" did this	I did this "infrequently"	I did this "inconsistently"	I did this "frequently"	I did this "always"
1. I asked myself periodically if I was meeting my goals.	○	○	○	○	○
2. I considered several alternatives to a problem before I answered.	○	○	○	○	○
3. I tried to use strategies that had worked in the past.	○	○	○	○	○
4. I paced myself while learning in order to have enough time.	○	○	○	○	○
5. I understood my intellectual strengths and weaknesses.	○	○	○	○	○
6. I thought about what I really needed to learn before I began a task.	○	○	○	○	○
7. I knew how well I did once I finished a test.	○	○	○	○	○
8. I set specific goals before I began a task.	○	○	○	○	○
9. I slowed down when I encountered important information.	○	○	○	○	○
10. I knew what kind of information was most important to learn.	○	○	○	○	○
11. I asked myself if I had considered all options when solving a problem.	○	○	○	○	○
12. I was good at organising information.	○	○	○	○	○
13. I consciously focused my attention on important information.	○	○	○	○	○

Appendix Figure 8: Post-MAI Survey Question (14-26)

14. I had a specific purpose for each strategy I used.	○	○	○	○	○
15. I learned best when I knew something about the topic.	○	○	○	○	○
16. I knew what the teacher expected me to learn.	○	○	○	○	○
17. I was good at remembering information.	○	○	○	○	○
18. I used different learning strategies depending on the situation.	○	○	○	○	○
19. I asked myself if there was an easier way to do things after I finished a task.	○	○	○	○	○
20. I had control over how well I learned.	○	○	○	○	○
21. I periodically reviewed to help me understand important relationships.	○	○	○	○	○
22. I asked myself questions about the material before I began.	○	○	○	○	○
23. I thought of several ways to solve a problem and chose the best one.	○	○	○	○	○
24. I summarised what I've learned after I finished.	○	○	○	○	○
25. I asked others for help when I didn't understand something.	○	○	○	○	○
26. I could motivate myself to learn when I needed to.	○	○	○	○	○

Appendix Figure 9: Post-MAI Survey Question (27-39)

	I "never" did this	I did this "infrequently"	I did this "inconsistently"	I did this "frequently"	I did this "alway
27. I was aware of what strategies I used when I studied.					
28. I considered several alternatives to a problem before I answered.					
29. I used my intellectual strengths to compensate for my weaknesses.					
30. I focused on the meaning and significance of new information.					
31. I created my own examples to make information more meaningful.					
32. I was a good judge of how well I understood something.					
33. I found myself using helpful learning strategies automatically.					
34. I found myself pausing regularly to check my comprehension.					
35. I knew when each strategy I used would be most effective.					
36. I asked myself how well I accomplished my goals once I was finished.					
37. I drew pictures or diagrams to help me understand while learning.					
38. I asked myself if I had considered all options after I solved a problem.					
39. I tried to translate new information into my own words.					

Appendix Figure 10: Post-MAI Survey Question (40-52)

40. I changed strategies when I failed to understand.	○	○	○	○	○
41. I used the organisational structure of the text to help me learn.	○	○	○	○	○
42. I read instructions carefully before I began a task.	○	○	○	○	○
43. I asked myself if what I was reading was related to what I already knew.	○	○	○	○	○
44. I re-evaluated my assumptions when I got confused.	○	○	○	○	○
45. I organised my time to best accomplish my goals.	○	○	○	○	○
46. I learned more when I was interested in the topic.	○	○	○	○	○
47. I tried to break studying down into smaller steps.	○	○	○	○	○
48. I focused on overall meaning rather than specifics.	○	○	○	○	○
49. I asked myself questions about how well I was doing while I was learning something new.	○	○	○	○	○
50. I asked myself if I learned as much as I could once I finished a task.	○	○	○	○	○
51. I stopped and went back over new information that was not clear.	○	○	○	○	○
52. I stopped and re-read when I got confused.	○	○	○	○	○

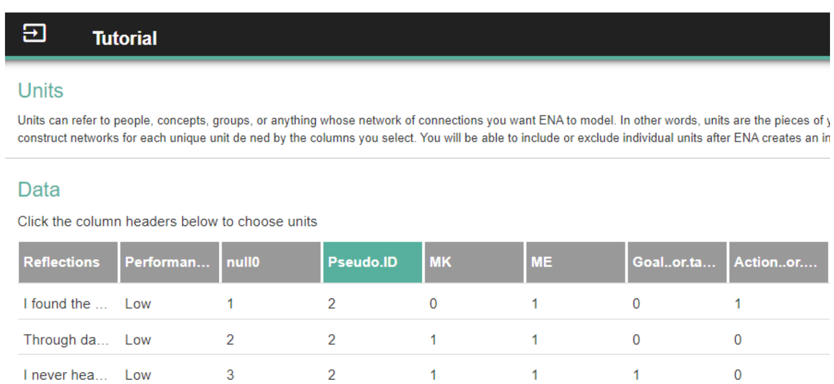
F. Steps for Epistemic Network Analysis in ENA Webtool

The Epistemic Network Analysis (ENA) was performed using the ENA web tool. The following snippets in Appendix Figure 11 contains the four steps performed for retrieving the network models of high and low-score students.

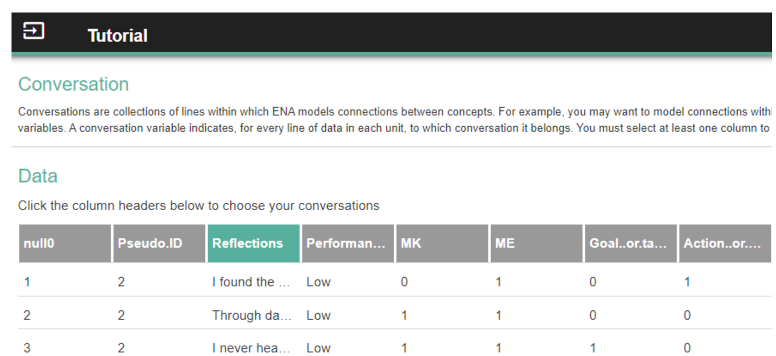
The first step was selecting the "units" that were "pseudo-ID" for this study. The next step is selecting the conversation. As we analysed students' written reflections, we found that they were "reflections" for this research. The third step in the process was selecting the "stanza window". We primarily selected "4" and then changed it to "whole conversation" later from the "advanced" section. The fourth step was selecting the code. As we adapted Flavell's (1979) framework, it was "MK", "ME", "Goals (or tasks)", and "Actions (or strategies)". Lastly, for comparison, we compared high- and low-score students and selected the "performance group" comparison. After performing all these steps, network models were created for high and low-score students.

Appendix Figure 11: Steps Performed for ENA

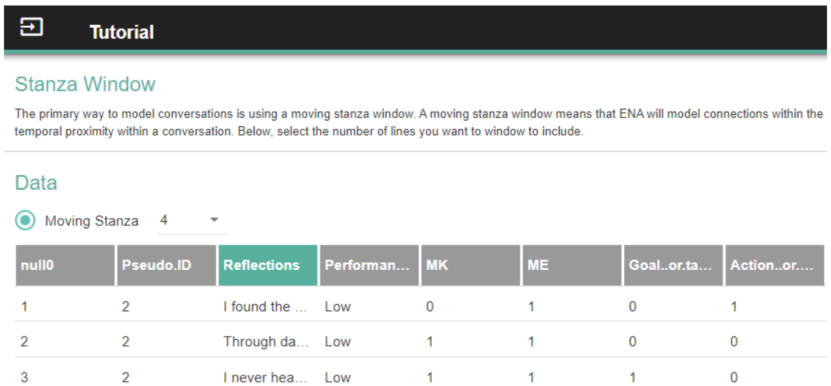
Step 1: Selecting "Units" – "Pseudo-ID"



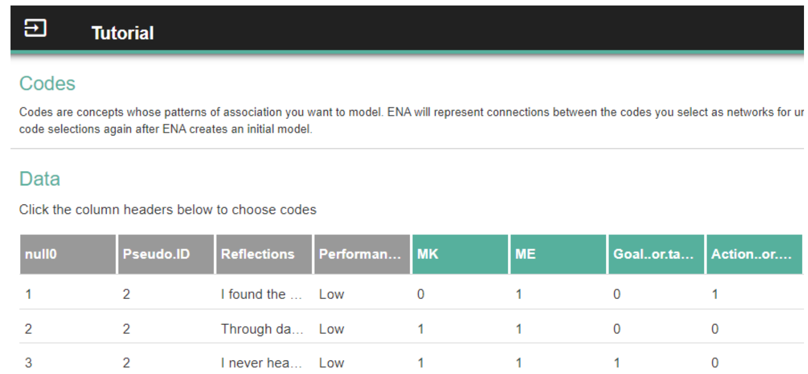
Step 2: Selecting "Conversation" – "Reflections"



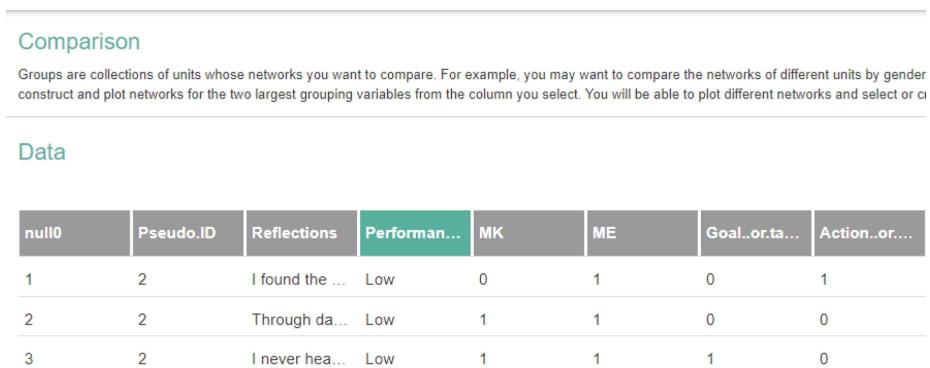
Step 3: Selecting "Stanza Window" – "Whole Window"
(selecting Stanza window of "4" first, then changing from the advanced option later)



Step 4: Selecting "Code" – "MK, ME, Goals or tasks, Actions or strategies"



Step 4: Selecting "Comparison" – "Performance Group"

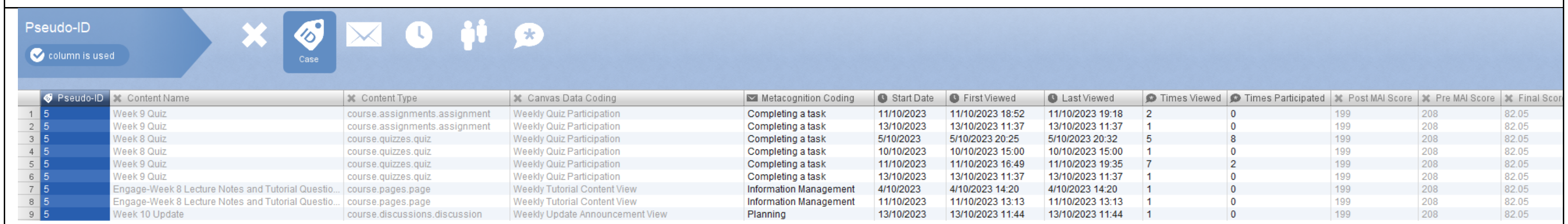


G. Steps for Process Mining in Disco

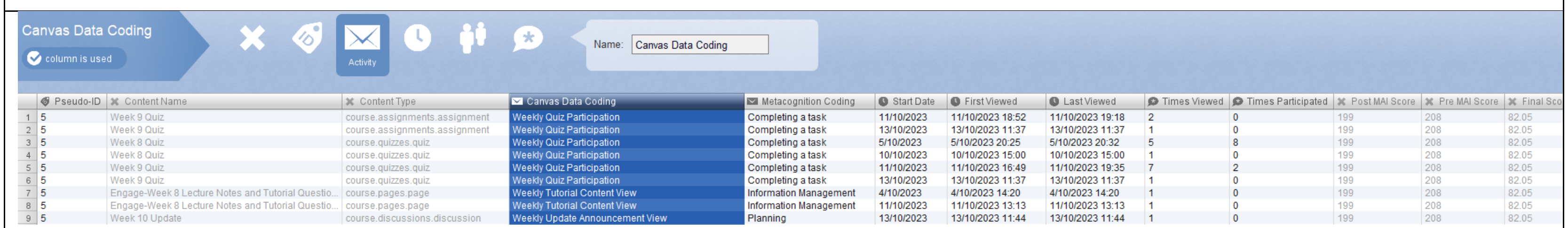
The following snippets in Appendix Figure 12 represents the steps performed for process mining in Disco.

Appendix Figure 12: Steps in Disco for Process Mining

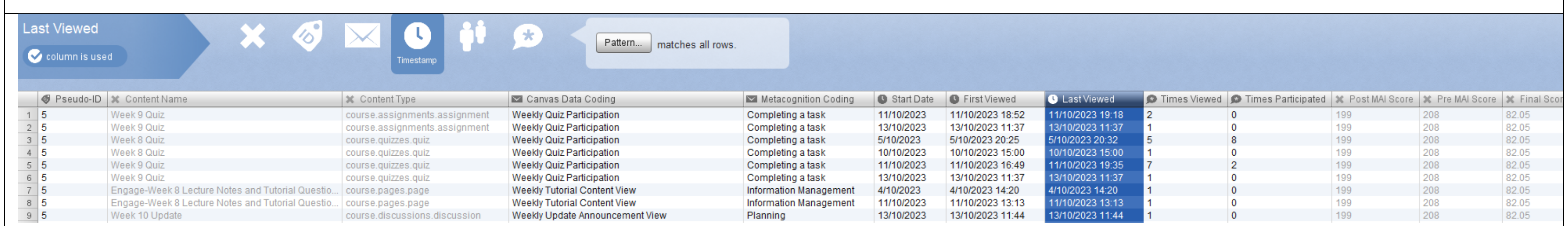
Step 1: Selecting Case – "Pseudo-ID"



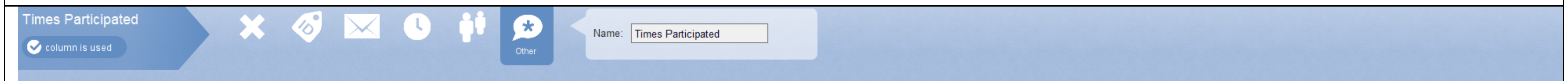
Step 2: Selecting Activity – "Canvas Data Coding" and "Metacognition Coding"



Step 3: Selecting Timestamp – "First Viewed" and "Last Viewed"



Step 4: Selecting Other – "Times Viewed" and "Times Participated"



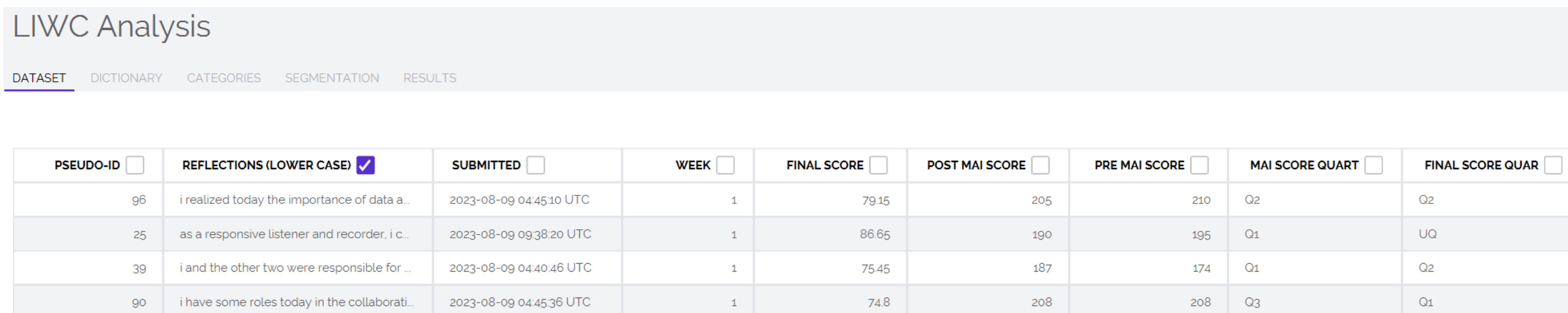
	Pseudo-ID	Content Name	Content Type	Canvas Data Coding	Metacognition Coding	Start Date	First Viewed	Last Viewed	Times Viewed	Times Participated	Post MAI Score	Pre MAI Score	Final Scor
1	5	Week 9 Quiz	course.assignments.assignment	Weekly Quiz Participation	Completing a task	11/10/2023	11/10/2023 18:52	11/10/2023 19:18	2	0	199	208	82.05
2	5	Week 9 Quiz	course.assignments.assignment	Weekly Quiz Participation	Completing a task	13/10/2023	13/10/2023 11:37	13/10/2023 11:37	1	0	199	208	82.05
3	5	Week 8 Quiz	course.quizzes.quiz	Weekly Quiz Participation	Completing a task	5/10/2023	5/10/2023 20:25	5/10/2023 20:32	5	8	199	208	82.05
4	5	Week 8 Quiz	course.quizzes.quiz	Weekly Quiz Participation	Completing a task	10/10/2023	10/10/2023 15:00	10/10/2023 15:00	1	0	199	208	82.05
5	5	Week 9 Quiz	course.quizzes.quiz	Weekly Quiz Participation	Completing a task	11/10/2023	11/10/2023 16:49	11/10/2023 19:35	7	2	199	208	82.05
6	5	Week 9 Quiz	course.quizzes.quiz	Weekly Quiz Participation	Completing a task	13/10/2023	13/10/2023 11:37	13/10/2023 11:37	1	0	199	208	82.05
7	5	Engage-Week 8 Lecture Notes and Tutorial Questio...	course.pages.page	Weekly Tutorial Content View	Information Management	4/10/2023	4/10/2023 14:20	4/10/2023 14:20	1	0	199	208	82.05
8	5	Engage-Week 8 Lecture Notes and Tutorial Questio...	course.pages.page	Weekly Tutorial Content View	Information Management	11/10/2023	11/10/2023 13:13	11/10/2023 13:13	1	0	199	208	82.05
9	5	Week 10 Update	course.discussions.discussion	Weekly Update Announcement View	Planning	13/10/2023	13/10/2023 11:44	13/10/2023 11:44	1	0	199	208	82.05

H. Steps for Natural Language Processing in LIWC

The following snippets in Appendix Figure 13 represents the steps performed in LIWC for extracting the linguistic features from students' written reflections.

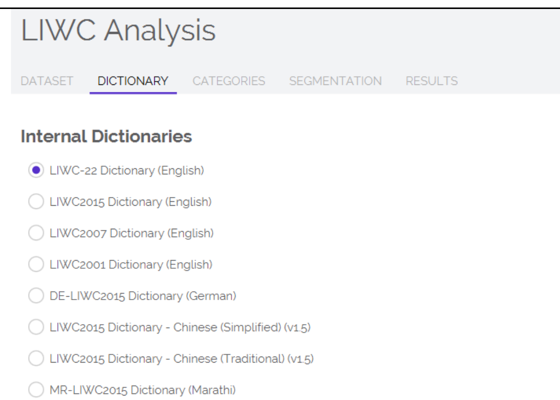
Appendix Figure 13: Steps for LIWC

Step 1: Selecting the dataset and column for analysis

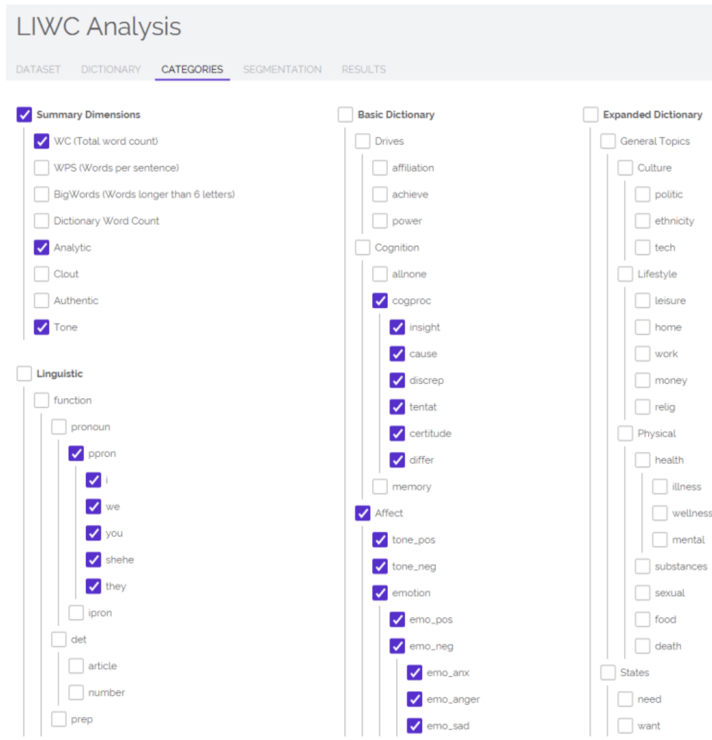


PSEUDO-ID	REFLECTIONS (LOWER CASE)	SUBMITTED	WEEK	FINAL SCORE	POST MAI SCORE	PRE MAI SCORE	MAI SCORE QUART	FINAL SCORE QUAR
96	i realized today the importance of data a...	2023-08-09 04:45:10 UTC	1	79.15	205	210	Q2	Q2
25	as a responsive listener and recorder, i c...	2023-08-09 09:38:20 UTC	1	86.65	190	195	Q1	UQ
39	i and the other two were responsible for ...	2023-08-09 04:40:46 UTC	1	75.45	187	174	Q1	Q2
90	i have some roles today in the collaborati...	2023-08-09 04:45:36 UTC	1	74.8	208	208	Q3	Q1

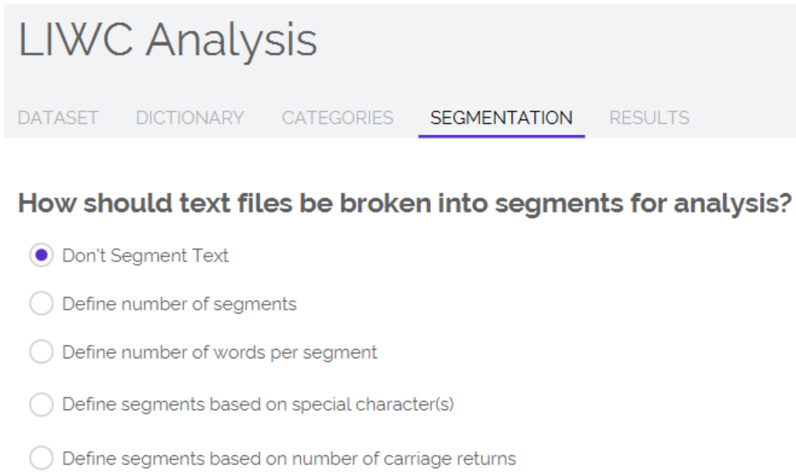
Step 2: Selecting the appropriate dictionary



Step 3: Selecting the required categories for analysis



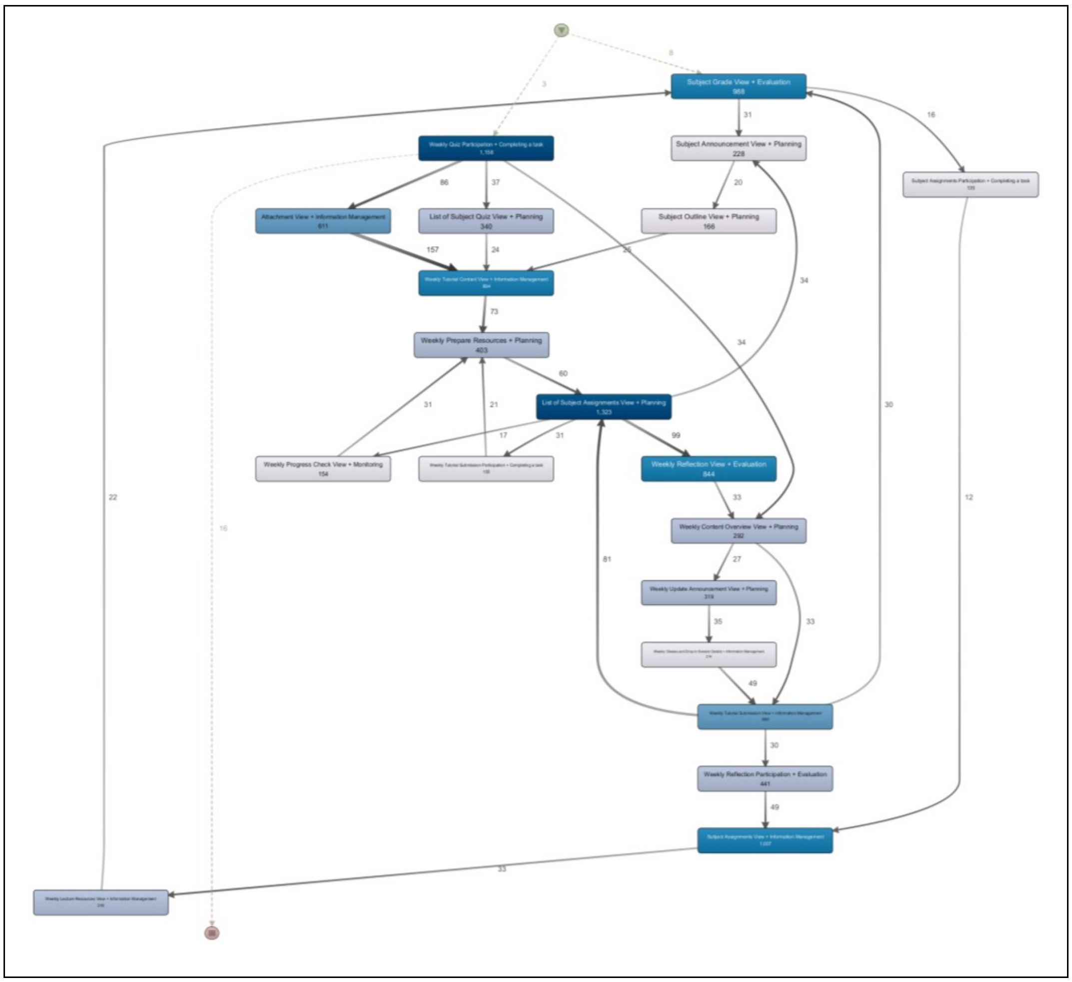
Step 4: Selecting the preferred segmentation



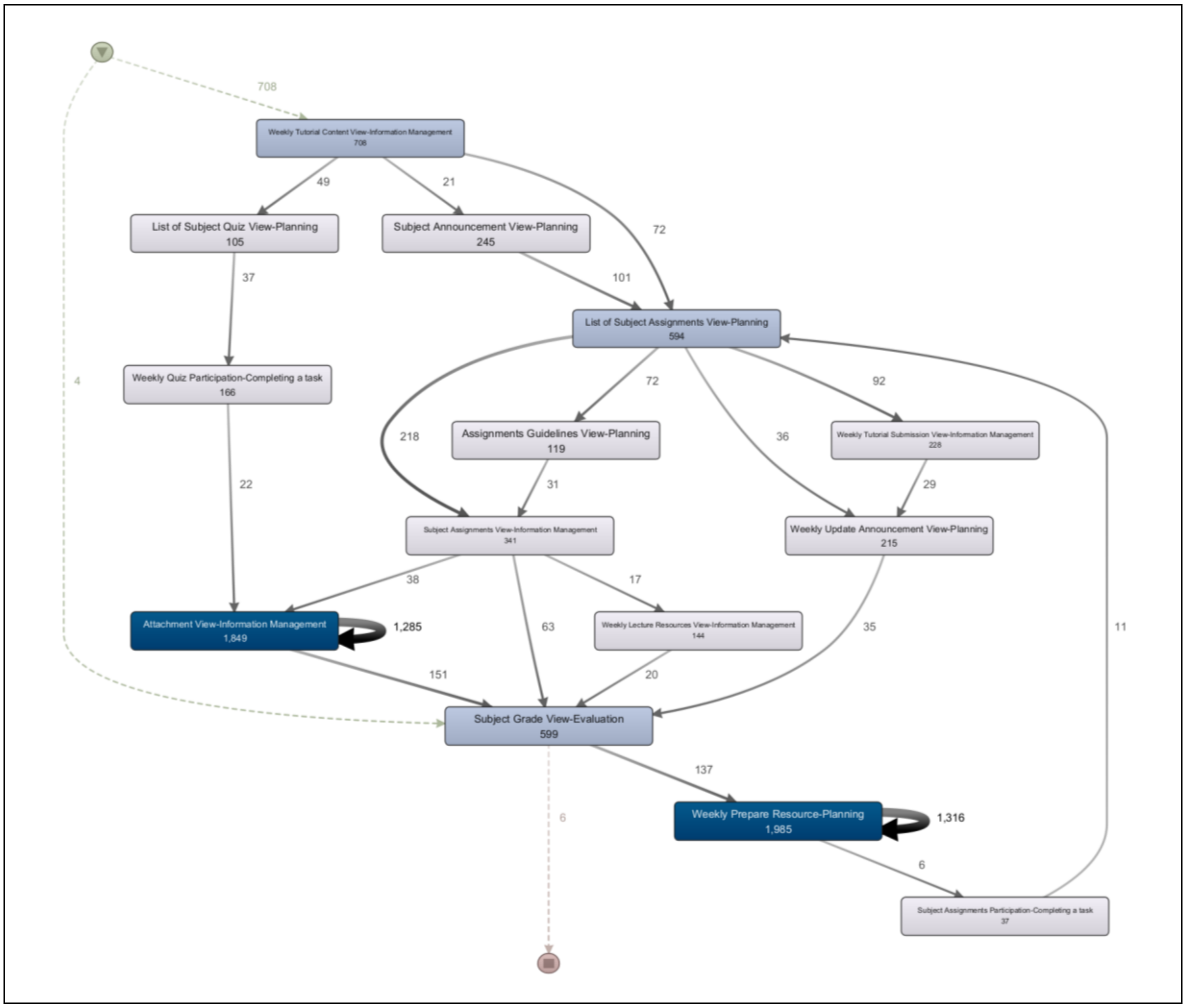
I. Complete Graphs of Students' Process Models

The following Appendix Figure 14 and Appendix Figure 15 represent the process models of students who received the intervention (Appendix Figure 14) and those who did not (Appendix Figure 15). Due to their extensive size, readers of this document are encouraged to "zoom in" for better readability.

Appendix Figure 14: Process Model of IT-04 (students who experienced the intervention)



Appendix Figure 15: Process Model of IT-05 (students who did not experience the intervention)



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