Development and Implementation of a Learning Analytics Tool to Support Teacher Orchestration of Collaborative Science Inquiry in a Mobile Learning Environment

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Abstract

Keywords: Teacher orchestration, Collaborative Science Inquiry (CSI), Mobile Learning Environments (MLEs), Theory-led design, Learning Analytics (LA)

Statement of originality

I, Jiaxin CAO, hereby declare that I am the sole author of the thesis, and the material presented in this thesis is my origin except those indicated in the acknowledgment. I further declare that I have followed the University's policies and regulations on Academic Honesty, Copyright, and Plagiarism in writing the thesis, and no material in this thesis has been submitted for a degree in this or other universities.

Abstract

Collaborative Science Inquiry (CSI) is a pedagogical approach that fosters students' scientific skills and competencies through group-based inquiry activities. However, CSI poses various challenges for teachers (i.e., recognizing the problems and needs of each group, identifying appropriate strategies to address them, and reviewing the impact of these strategies) to support students' learning process across different contexts and social levels, especially in a Mobile Learning Environment (MLE). To address this problem, this study adopted Design-Based Research (DBR), aiming to design, develop, implement, and evaluate a theory-led LA tool on a mobile app, namely, the m-Orchestrate app to support teacher orchestration in CSI. The tool aligns with the inquiry cycle model and provides teachers with real time data and feedback on students' inquiry progress, collaboration, and learning outcomes. The DBR lasted three years, involving four phases, including (1) Phase I: Analysis of practical problems in orchestrating CSI in an MLE, (2) Phase II: Design and development of a theory-led LA tool, (3) Phase III: Three iterative cycles of testing and refining the LA tool in practice, and (4) Phase IV: Reflection and further implementation of the LA tool. The researcher collaborated with two primary schools, four teachers, two pre-service teachers in General Studies, and around 250 students in Grade 4 in Hong Kong. The research questions focused on (1) investigating the affordances of the LA tool with theory-led and interactive design for teacher orchestration of CSI; (2) the impact of the tool on teacher orchestration in CSI; and (3) the impact of teacher orchestration supported by the tool on student performance in CSI. Data collection included log data from the LA tool and the m-Orchestrate app, teacher interviews, and students' pre- and post-quizzes. Both qualitative and quantitative data analysis methods were adopted. The research findings show that (1) the affordances of the developed LA tool include interactive features with just-in-time orchestration, Business Process Analytics in R (bupaR) (Janssenswillen et al., 2019) features to visualize students' CSI process in real time, and Python implementation of the Bayesian Knowledge Tracing (pyBKT) (Anirudhan et al., 2021) features to identify highly-related behaviors to phase completion of CSI learning from previous projects; (2) the LA tool could help teacher orchestrate CSI effectively; and (3) teacher orchestration using the LA tool could help enhance student performance in CSI. The LA features of the LA tool provided a deeper understanding of students' CSI learning processes for evidence-based orchestration practice. The significance of the study lies in three aspects. First, theoretically, the theory-led LA tool, a process model of the LA-enhanced orchestration, and design principles contribute to LA-enhanced teacher orchestration CSI in an MLE. Secondly, technically, the technical design and development of the theory-led LA tool with the three affordances for teacher orchestration in CSI in an MLE can shed light on future LA tool development. Thirdly, practically, the approach of integrating the LA tool into teaching and learning in CSI in an MLE could effectively enhance teacher orchestration and students' performance, an area rarely explored in the literature. Limitations and future work are also discussed for further design, development, and implementation of LA-enhanced teacher orchestration of CSI in an MLE.

Keywords: Teacher orchestration, Collaborative Science Inquiry (CSI), Mobile Learning Environments (MLEs), Theory-led design, Learning Analytics (LA)

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Contents

List of Abbreviations

CSI Collaborative Science Inquiry

LA Learning Analytics

MLE Mobile Learning Environment

CSCL Computer-Supported Collaborative Learning

RQ Research Question

DBR Design-Based Research

EDM Educational Data Mining

COVID-19 Coronavirus Disease 2019

pyBKT Python implementation of the Bayesian Knowledge Tracing

bupaR Business Process Analytics in R

KWL Know-Want-Learned

LLM Large Language Model

GBA Greater Bay Area

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Chapter 1: Introduction

1.1 Background

In the 21st century, students are expected to be equipped with various skills and competencies through the science-learning experience, which includes problem solving, collaboration, and computational thinking (Chu et al., 2012). Underpinned by social constructivist theories (Vygotsky, 1978) as an inquiry-based learning model, Collaborative Science Inquiry (CSI) encourages students to form inquiry groups to tackle interesting questions, collect evidence, analyze materials, explain their outcomes, and reflect on their exploration process. Students need various tools and resources during the CSI learning process. According to the fourth strategy on information technology in education (Bureau, 2015), various educational technologies have been introduced to support students' learning in CSI. However, it is challenging for students to remain productive and complete these goals in CSI, especially in the early collaborative inquiry stage (Arnseth & Krange, 2016).

Consequently, teachers' support is critical to the success of students' CSI learning. As one of the most challenging and exciting ventures for teachers' practice (Phua, 2013), CSI requires greater competency from teachers in managing a collaborative learning environment. Teachers need support in dealing with a range of complex factors, such as multiple social levels and cross-contexts, in CSI pedagogical practices. With the increasing popularity of mobile technology in current learning practices, Computer-Supported Collaborative Learning (CSCL) also enables inquiry activities beyond the classroom (Bell et al., 2010) and presents more challenges for teachers' orchestration of CSI. For instance, teachers may face difficulties in monitoring and regulating students' online behavior and motivation when they use technology for CSI learning.

Based on the rich educational data produced by CSCL contexts, Learning Analytics (LA) and Educational Data Mining (EDM) approaches have the potential to assist teachers in monitoring and intervening on the fly across learning settings (Gašević, Dawson & Pardo, 2016). EDM and LA are two distinct yet related fields that focus on leveraging data to improve education (Siemens & d Baker, 2012). While they share similarities, they differ in their primary objectives and approaches.

EDM is concerned with developing tools, techniques, and methodologies for collecting, aggregating, and analyzing large educational datasets (Berland et al., 2014). It emphasizes applying data mining techniques to extract meaningful insights from educational data (Aldowah et al., 2019). EDM aims to identify patterns, relationships, and trends in educational contexts to support decision-making processes (Slater et al., 2017). It focuses on the discovery of new knowledge about learning and teaching processes.

LA can apply EDM findings to improve educational interactions and learning experiences. LA aims to enhance educational practices by providing actionable insights derived from data analysis(Papamitsiou & Economides, 2014). It emphasizes using analytics techniques to inform instructional design, personalized learning experiences, and student support systems (Yilmaz & Yilmaz, 2020).

However, the information provided by most LA tools is mainly statistical and data-driven, which is challenging to interpret for pedagogical decisions (Schwendimann et al., 2017). These tools, which are specially designed for teachers, mainly focus on the post-reflection of instructional practices (Pelánek, 2020). Some recent LA tools (Matuk et al., 2019; van Leeuwen et al., 2019) align with collaborative inquiry theories to make data interpretation easier; however, they still lack the capacities to demonstrate CSI's learning trajectories or to suggest interventions across social levels and learning contexts.

The m-Orchestrate app [as a web platform previously (Song et al., 2019)] is a mobile learning app developed by the research team at the Education University of Hong Kong, where the researcher is involved. It enables teacher orchestration and student CSI in a Mobile Learning Environment (MLE). The app incorporates mobile technology into the science curriculum and supports inquiry activities, collaboration, and inquiry-based pedagogy based on social constructivist theories. It offers a user-friendly interface that makes students easy to engage, collect, analyze, explain, and reflect on inquiry processes. From previous studies (Song et al., 2022), users can improve and enhance their group-based inquiry processes for optimal effectiveness, leading to deeper understanding and richer outcomes by using the m-Orchestrate app. However, the m-Orchestrate app still has the potential to provide more meaningful and deep information for teachers' orchestration practices by the theory-led design of LA approaches.

Theory-led design is an approach to developing LA tools that are based on first principles derived from educational theories (Kelly et al., 2015). To explore the potential of LA technology for supporting teacher orchestration in group-based CSI learning within and beyond the classroom, this study proposes to design a theory-led LA tool by considering the nature of CSI teaching and learning to support teachers' monitoring of CSI processes and "just-in-time" pedagogical decision making in an MLE that simultaneously can help improve students' CSI.

1.2 Research Objectives

Against the aforementioned background, the research objectives of this study are as follows:

1. To design and develop a theory-led Learning Analytics (LA) tool on the m-Orchestrate app for teacher orchestration of CSI,
2. To investigate the impact of the proposed LA tool on teacher orchestration in facilitating CSI, and
3. To evaluate the impact of teacher orchestration supported by the proposed LA tool on students' performance in Collaborative Science Inquiry (CSI) in an Mobile Learning Environment (MLE).

To address these objectives, this study formulated three research questions (RQs) that guided the design, development, implementation and evaluation of the theory-led LA tool on the m-Orchestrate app. The RQs were derived from the theoretical foundation and the literature review of this work, and they aimed to explore the use and impact of the LA tool for teacher orchestration of CSI in an MLE.

1.3 Research Questions

This study aimed to explore the use of a Learning Analytics (LA) tool for theory-led and interactive design for the teacher orchestration of Collaborative Science Inquiry (CSI) in an Mobile Learning Environment (MLE). The following Research Questions (RQs) were explored.

RQ1: What were the affordances of the LA tool for theory-led and interactive design for the teacher orchestration of CSI in an MLE?

RQ2: What was the impact of the theory-led LA tool on teachers' orchestration of CSI in an MLE?

RQ3: What was the impact of teacher orchestration supported by the theory-led LA tool on students' CSI performance in an MLE?

The RQ1 focused on the affordances of the LA tool for theory-led and interactive design for teacher orchestration of CSI. The aim was to create a theory-led LA tool underpinned by theoretical foundation that informed the principles, methods, and tools for enabling CSI in an MLE. The RQ2 examined the impact of the theory-led LA tool on teachers' orchestration of CSI in an MLE. The aim was to examine how the LA tool improved teachers' orchestration practices in enabling CSI, using a framework that explored how digital tools and LA could assist teacher orchestration practices in CSI in an MLE. The RQ3 investigated the impact of teacher orchestration supported by the theory-led LA tool on students' CSI performance. The aim was to evaluate how teacher orchestration supported by the LA tool enhanced students' performance in CSI in an MLE, using a data-driven approach that tracked and measured student progress in real time.

These RQs and ROs were significant for advancing LA approaches for supporting teacher orchestration in group-based CSI learning within and beyond the classroom. The next subsection presented the research contributions of this work in more detail.

1.4 Research Contributions

This research contributes to the literature on teacher orchestration in three aspects. First, theoretically, this new theory-led Learning Analytics (LA) tool was developed based on constructivist theories for science teachers to orchestrate Collaborative Science Inquiry (CSI) in primary schools, an area that few studies have delved into. A process model of the LA-enhanced orchestration of students' CSI in the Mobile Learning Environment (MLE) process was identified, and a set of design principles of an LA tool to support the teacher orchestration of students' CSI in an MLE was developed. Secondly, technically, the technical design and development of the theory-driven LA tool with the three affordances for teacher orchestration of CSI in an MLE can shed light on future LA tool development. Thirdly, practically, this study investigated the effectiveness of the approach by integrating the theory-led LA tool into teacher orchestration of CSI both inside and outside the classroom, which, in turn, helped students improve their performance, an area rarely explored in the literature. The pedagogical practices with the LA tool can be scaled up in more of Hong Kong's even Greater Bay Area (GBA)'s primary schools for effective teacher orchestration of CSI in an MLA.

The following section outlines the structure of this dissertation and summarizes the main contents of each chapter.

1.5 Structure of This Dissertation

The dissertation consists of eight chapters, organized as follows:

Chapter 1: Introduction. This chapter introduces the background, research objectives, research contributions, and research questions of the study. It also provides an overview of the Design-Based Research (DBR) methodology and its rationale.

Chapter 2: Literature Review. This chapter reviews the relevant literature on Collaborative Science Inquiry (CSI) learning, orchestration within and beyond the classroom, data analysis strategies to explore the CSI learning process, the technology-enhanced orchestration of CSI, and issues with implementing LA tools in current orchestration practice. It identifies research gaps and proposes a theoretical framework to guide the design of the Learning Analytics (LA) tool.

Chapter 3: Research Methodology. This chapter describes the DBR methodology in detail, including its phases, activities, data collection and analysis methods, and ethical considerations. It also explains how DBR is suitable for addressing the research questions and aims of this study.

Chapter 4: Implementation of Design-based Research. This chapter reports on the implementation of each phase of DBR methodology, including the analysis of practical problems in orchestrating CSI in an Mobile Learning Environment (MLE), the refinement of the m-Orchestrate app and development of a theory-led LA tool, and the iterative cycles of testing and refinement of the tool in practice. It presents the data collection and analysis procedures, results, and reflections for each cycle.

Chapter 5: Discussions. This chapter discusses the main findings of this study, based on the data analysis results from each cycle. The discussions centered around (1) the theory-driven

LA Tool design and development for teacher orchestration of student CSI in a MLE, (2) the technical design and development of the LA tool with the three affordances for teacher orchestration of CSI in an MLE, (3) approaches of integrating the theory-led LA tool into teacher orchestration of student CSI in an MLE, and (4) theoretical, practical, and technical contributions of the study.

Chapter 6: Conclusions. This chapter summarizes the main findings and contributions of this study, answers the research questions and aims, reflects on the limitations and challenges encountered during this study, and suggests directions for future work.

Chapter 7: Limitations. This chapter acknowledges the limitations of this study, such as sample size, generalizability, validity, reliability, and technical issues.

Chapter 8: Future Work. This chapter proposes possible extensions or improvements for this study, such as conducting more cycles with different participants or contexts, exploring other data analysis methods or models, integrating other features or functionalities into the LA tool, or evaluating its long-term impact or sustainability.

This dissertation adopted a DBR approach that combined theoretical insights with practical interventions to design, develop, implement, and evaluate a theory-led LA tool for teacher orchestration of CSI in an MLE. The next chapter will review the relevant literature on this topic.

Chapter 2: Literature Review

As mentioned in the previous chapter, science teachers face various challenges in conducting students' Collaborative Science Inquiry (CSI) learning in a Mobile Learning Environment (MLE). Learning Analytics (LA) and Educational Data Mining (EDM) technologies can potentially support their "just-in-time" pedagogical decisions. This chapter outlines (1) pupils' needs and challenges for teachers in the CSI learning context, (2) orchestration principles as guidelines for teachers to manage the CSI learning context, (3) LA technologies and their applications in supporting teacher orchestration in previous research, and (4) teachers' needs for orchestrating LA tools. Finally, the issues and challenges of the research are identified for supporting teachers' orchestration of CSI.

2.1 Collaborative Science Inquiry Learning

Collaborative Science Inquiry (CSI) learning has gained attention in educational research (Aldowah et al., 2019; Alonso-Fernandez et al., 2020; Scardamalia, 2002). When students learn through CSI, they can collaborate to create, find, and improve new knowledge, which can help them learn more than they would on their own (Scardamalia, 2002). Such environments enable students to participate in hands-on activities, pose inquiries, and seek evidence-based explanations, fostering critical thinking and problem-solving skills (Abdi, 2014; Berland et al., 2015; G. W. Chen, 2020).

2.1.1 Inquiry-Based Learning

CSI learning underpins the inquiry-based learning model, which is grounded in a socio-constructivist theory (Vygotsky, 1978), and posits that a student studies science much as a scientist would, in a collaborative and inquiry-based way (Minner et al., 2010). Social constructivism recognizes the uniqueness of learners and emphasizes productive interactions among peers in collaborative learning (Wertsch, 1985).

Collaborative learning encourages students to take ownership of their learning process, fosters deeper understanding through active engagement, and cultivates skills that extend beyond the knowledge of the subject matter (Amarasinghe et al., 2022). Conversely, in the traditional approach, students passively receive scientific knowledge through direct instruction, which hinders the development of essential skills for the 21st century, such as problem solving, collaboration, and critical thinking (Boyatzis & Boyatzis, 2008; Mascolo & Fischer, 2005).

Generally, the inquiry-based learning model consists of five phases: engage, explore, analyze, explain, and reflect. It focuses on developing students' scientific thinking and collaborative skills, such as questioning, critical thinking, and problem solving (Savery, 2015). The 5E (Engage, Explore, Explain, Elaborate, and Evaluate) models have been commonly adopted throughout the decades to promote scientific inquiry (Bybee et al., 2006). Students are actively engaged in the learning process, with the teacher serving as a facilitator and guide (Skrypnyk et al., 2015).

2.1.2 Collaborative Science Inquiry

CSI learning has emerged as a highly effective instructional approach, promoting active engagement, critical thinking, and problem-solving skills among students across different contexts supported by mobile technologies (Alonso-Fernandez et al., 2020; Berland et al., 2015; G. W. Chen, 2020). This pedagogical method encourages students to explore scientific concepts through hands-on investigations, posing questions, and seeking evidence-based explanations.

By engaging in CSI learning, students develop a deep understanding of scientific concepts and processes as they actively construct knowledge through experimentation, analysis, and reflection (Berland et al., 2015). As a student-centered approach, inquiry-based learning not only enhances content knowledge but also nurtures valuable skills, such as collaboration, communication, and an inquiry mindset (G. W. Chen, 2020).

Moreover, CSI aligns with the authentic practices of scientific inquiry, providing students with opportunities to think as scientists do and engage in the processes of scientific discovery (Berland et al., 2015). Through a combination of guided inquiry, open exploration, and structured investigations, CSI learning empowers students to become active participants in their learning, fostering a lifelong passion for science and a deeper appreciation of the scientific method (G. W. Chen, 2020).

2.1.3 Collaborative Science Inquiry in a Mobile Learning Environment

Collaborative Science Inquiry (CSI) in a Mobile Learning Environment (MLE) implements information technologies to enable more student initiatives during the scientific inquiry process (Berland et al., 2013; Li et al., 2018). The proliferation of Computer-Supported Collaborative Learning (CSCL) empowers their inquiry-related activities and brings learners technical solutions for sharing information, communicating, and collaborating in groups on their initiatives to achieve common goals (Bell et al., 2010). This CSI pedagogical approach in an MLE emphasizes the active engagement of students in scientific investigations through collaboration and the use of mobile devices (Aldowah et al., 2019; Alonso-Fernandez et al., 2020). For example, ViLLE (Laakso et al., 2018) integrates various tools and principles to enhance students' engagement and motivation in the learning process.

CSI in an MLE offers several advantages over a traditional classroom setting. Firstly, mobile learning enables students to engage in scientific inquiry beyond the confines of the classroom, allowing them to explore real-world phenomena and conduct experiments in their environment (Zhu & Wang, 2020). This hands-on approach fosters a deeper understanding of scientific concepts and encourages students to develop critical thinking skills. Secondly, mobile devices provide access to a wealth of information and resources, such as online databases and scientific journals, which can enhance the quality of research conducted by students (Quan et al., 2022). Moreover, mobile learning facilitates student collaboration, enabling them to collaborate on projects and share ideas more easily (L. Chen et al., 2020). This collaborative aspect of mobile learning promotes teamwork and communication skills, which are essential for success in scientific inquiry. Finally, mobile learning offers greater flexibility regarding time and location, allowing students to engage in scientific inquiry at their own pace and convenience (Song et al., 2022).

2.1.4 Challenges of Collaborative Science Inquiry in a Mobile Learning Environment

In CSI, it is difficult to ensure that small groups reach their common goals because they can lose focus or motivation without continuous engagement during CSCL (Webb, 2009). Therefore, the teacher plays a vital role (Gillies et al., 2007) in promoting student interaction that is beneficial for collaborative learning (Gillies & Boyle, 2008).

As mentioned previously, CSI in an MLE is a complex context compared to traditional instructional learning settings. Therefore, teachers cannot simply rely on previous concerns to facilitate students' CSI learning in an MLE. They need further guidance on conveying strategies for facilitating students' CSI in an MLE (Marchal–Crespo et al., 2014). The valuable information for teachers to grasp the outcomes of students' CSI learning in an MLE includes more comprehensive insights into skill development via in-progress milestones, outcomes, and artifacts (e.g., performance assessments, portfolios, and self-assessments) (Linn et al., 2015).

Moreover, previous teaching strategies may not be able to adequately guide teachers on how to select or decide the appropriate pedagogical actions to help students solve problems in CSI (Abdi, 2014). Orchestration principles (Dillenbourg et al., 2011) have been developed over the past ten years to help teachers cope with the complex factors encountered in managing complex CSI learning activities in an MLE.

2.2 Teacher Orchestration Principles

Nowadays, class orchestration is regarded as a core competency of effective teaching in facilitating Collaborative Science Inquiry (CSI) (Bae et al., 2019; Knight et al., 2017). "Class orchestration" refers to the systematic and intentional management of learning activities within a classroom environment to support and enhance students' learning experiences (Dillenbourg, 2013; Dillenbourg et al., 2011). It is used interchangeably with "teacher orchestration." However, with the advent of online learning and the unforeseen circumstances brought about by the Coronavirus Disease 2019 (COVID-19) pandemic (Nasir et al., 2021), it is crucial to examine the concept of orchestration in both physical and online contexts (Zhu & Wang, 2020). The wider implementations of an Mobile Learning Environment (MLE) foster the meanings and explanatory compatibilities of orchestration principles beyond the classroom, such as creating synchronous and asynchronous activities that foster collaboration and engagement in an MLE (Berland et al., 2015). Students use tools for communication and collaboration to support group work, knowledge sharing, and discussions. The next section explores the current state of orchestration, considering its application within traditional classroom environments and its extension to virtual and remote learning settings.

2.2.1 Teacher Orchestration in the Classroom

Teacher orchestration involves the effective integration of pedagogical strategies, technological tools, and Learning Analytics (LA) to facilitate collaborative learning, monitor student progress, and provide timely interventions (Dillenbourg et al., 2011). Teacher orchestration encompasses various dimensions, including instructional design and the facilitation of collaborative learning on the fly. Dillenbourg and Jermann (2010) gathered 14 elements from the results of empirical studies related to teacher orchestration in assorted learning environments to indicate that pedagogical strategies are "working well." They are leadership, flexibility, control, integration, linearity, continuity, drama, physicality, awareness, design for all, curriculum relevance, assessment relevance, minimalism, and sustainability (Dillenbourg et al., 2011).

Effective teacher orchestration in the classroom offers several benefits for both teachers and students (Amarasinghe et al., 2022). By integrating technology and data-driven insights into teaching practices, teachers can make informed decisions about instructional strategies, interventions, and personalized support (McKenney & Mor, 2015; Worsley & Blikstein, 2014). LA dashboards provide real-time feedback on student's progress, enabling teachers to identify areas of improvement, anticipate challenges, and adapt their instruction accordingly (Han & Ellis, 2021; Saleh et al., 2022; Zheng et al., 2021). Moreover, teacher orchestration promotes collaboration, as students engage in group activities, discussions, and knowledge sharing, fostering social interactions and the development of teamwork skills (Berland et al., 2015; Nasir et al., 2021; Zhu & Wang, 2020).

By aligning with these principles, teachers can gain a deeper understanding of individual and collective learning processes, enabling them to tailor their instruction and interventions more effectively (Berland et al., 2014; Monroy et al., 2014; Taub & Azevedo, 2018). Teacher orchestration in the classroom employs a range of pedagogical approaches that foster active participation, collaboration, and reflection among students (Monroy et al., 2014).

Inquiry-based approaches underpinned by constructivist theories are commonly to develop learners' critical thinking, communication, and problem-solving skills (Taub & Azevedo, 2018). These approaches emphasize student-centered learning, where learners actively construct knowledge through exploration, discussion, and reflection (Alonso-Fernandez et al., 2019). Integrating technology tools and learning platforms has facilitated student-centered learning, offering scaffolding, feedback, and resources to support students' cognitive and social development (Yilmaz & Yilmaz, 2020). Teacher orchestration leverages technological tools and learning platforms to facilitate these pedagogical approaches, providing scaffolding, feedback, and resources for students' cognitive and social development (Hu et al., 2022; Yilmaz & Yilmaz, 2020).

While teacher orchestration holds promise for enhancing teaching and learning experiences, several challenges must be addressed. Privacy and ethical considerations regarding data collection and analysis require careful attention to ensure students' confidentiality and data security (Romero & Ventura, 2020). Teachers may also face challenges in effectively interpreting and utilizing the insights provided by LA tools, highlighting the importance of appropriate professional development and support (Er et al., 2021; Kasepalu et al., 2022; Zamecnik et al., 2022). Additionally, the design and implementation of teacher orchestration strategies should align with the specific educational context and the learner's characteristics to ensure effectiveness and relevance (Liang et al., 2022; Rosé & Järvelä, 2021; Sergis et al., 2019).

2.2.2 Teacher Orchestration of Collaborative Science Inquiry in Mobile Learning Environments

Historically, research on teacher orchestration has primarily focused on physical classroom settings in which teachers orchestrate activities, resources, and interactions to optimize student engagement and learning outcomes. Studies have examined the role of technology tools, such as LA dashboards and Educational Data Mining (EDM) techniques, to support teachers' orchestration efforts (Aldowah et al., 2019; Du et al., 2021; Koedinger et al., 2015). These technologies provide valuable insights into students' behavior, performance, and learning progress, enabling teachers to tailor their instruction and interventions effectively.

The COVID-19 pandemic has accelerated the adoption of online and Mobile Learning Environments (MLEs), necessitating the exploration of orchestration in virtual contexts. While the transition to online and mobile learning has posed significant challenges, it has also highlighted the potential of technology-mediated orchestration. Educators have utilized various digital tools, learning management systems, and video conferencing platforms to orchestrate online learning experiences in different contexts (Amarasinghe et al., 2022; McKenney & Mor, 2015; Worsley & Blikstein, 2014).

Teacher orchestration of Collaborative Science Inquiry (CSI) in a Mobile Learning Environment (MLE) requires additional considerations, such as designing asynchronous and synchronous activities that promote engagement and collaboration (Berland et al., 2015; Nasir et al., 2021; Zhu & Wang, 2020). Teachers leverage communication and collaboration tools to facilitate group activities, discussions, and knowledge sharing among students. LA in online environments provides real-time feedback on student's progress, allowing teachers to adapt their instruction and support individual needs (Han & Ellis, 2021; Saleh et al., 2022; Zheng et al., 2021). Moreover, privacy and ethical concerns related to data collection and analysis in online contexts necessitate careful attention to ensure students' confidentiality and data security (Romero & Ventura, 2020).

Previous studies (Dillenbourg, 2015; Gašević, Dawson, Rogers & Gasevic, 2016; Rodríguez-Triana et al., 2015) have identified three critical principles for orchestrating CSI in an MLE: awareness, continuity, and flexibility. Regarding teachers' "awareness," learning activities are spread across multiple settings and social levels, so it is difficult for them to be aware of the students' activity state at a behavioral level (Gašević, Dawson, Rogers & Gasevic, 2016). Consequently, teachers need a monitoring tool to enable them to review learners' participation and task completion rate in their learning process (Dillenbourg, 2015; Rodríguez-Triana et al., 2015).

In terms of the "continuity" of the learning activities in CSI, when the teacher observes problems in students' CSI, he/she must be able to identify the appropriate occasion to intervene and regulate students' learning to maintain a continuous flow of CSI (Slotta et al., 2013) to avoid interruptions or over-interventions (Tissenbaum & Slotta, 2019b).

Concerning "flexibility," the process of inquiry-based learning is not necessarily linear (Abrams et al., 2008). Accordingly, it is virtually impossible to prepare a "complete script" to predict CSI learning activities. Hence, pedagogical practices require higher teacher competency to enact technology-rich activities (Manathunga et al., 2015) with flexibility rather than over-scripting (Dillenbourg, 2002; Fong & Slotta, 2018). Therefore, the key to success in orchestrating CSI is understanding how to help teachers maintain their awareness of the student's learning status and take pedagogical action with continuity and flexibility.

2.2.3 Challenges for Teacher Orchestration of Collaborative Science Inquiry in a Mobile Learning Environment

Commonly, students' behaviors in CSI in an MLE usually occur among multiple stakeholders on specific phases or social levels across different contexts (Gašević, Dawson, Rogers & Gasevic, 2016). Correspondingly, it is problematic to obtain a bird's-eye view of them at a glance (Rodríguez-Triana et al., 2018).

Students might stray from their tasks, and teachers must be aware of this situation. Thus, such teaching needs during the teacher's orchestration of CSI present as awareness purposes, which are identified in some empirical studies (Dillenbourg, 2015; Rodríguez-Triana et al., 2015). Once being aware of the issue, the teacher must choose the appropriate way to redirect students' CSI learning in a productive direction to maintain the continuity of students' CSI learning process (Dillenbourg, 2013; Slotta et al., 2013). Otherwise, the issue may interrupt their inquiry progress and be less facilitation than over-intervention (Tissenbaum & Slotta, 2019b).

The CSI learning process is uncertain and not necessarily linear (Abrams et al., 2008). Consequently, it is almost impossible to prepare a "complete script" to predict or even direct CSI learning. To avoid "over-scripting" (Dillenbourg, 2002; Fong & Slotta, 2018), teachers need evidence to determine the just-in-time needs of students among technology-rich activities (Manathunga et al., 2015) and to enable them to intervene in their learning with flexibility.

In summary, teachers could encounter difficulties while orchestrating CSI in an MLE regarding (1) recognizing the problems and needs of each group and even the whole class's needs just in time, (2) identifying appropriate strategies to address students' issues and needs, (3) reviewing the impact of strategy on students' inquiry behavior, and (4) making sense of what to facilitate in the next step (Cao & Song, 2020). However, due to the complex and multi-threading process of students' CSI in an MLE (Dimitriadis, 2012), it can still be challenging for teachers to intervene in students' CSI in an MLE in time, even equipped with class orchestration principles. CSI learning activities in an MLE can occur across learning settings (such as online and offline) (Suárez et al., 2018) and social levels (e.g., class, group, and individual) (Jones et al., 2013). Additionally, learners are given opportunities to explore problems and take multiple pathways to arrive at a solution (Munneke et al., 2007).

Assisting with orchestration has gained significant attention in the EDM and LA fields as researchers and educators seek to optimize the learning process and improve instructional outcomes. The orchestration process involves interaction among such factors as rapidly changing contexts, novel pedagogy, support for learners' collaboration, monitoring, and assessing students' learning process and outcomes. For example, Bae et al. (2019) propose intelligent cognitive assistants or learning systems to support teacher orchestration with multimodal LA and data-rich feedback.

2.3 Learning Analytics and Educational Data Mining in Collaborative Science Inquiry

Learning Analytics (LA) and Educational Data Mining (EDM) are interdisciplinary fields of study concerned with developing methods for analyzing and interpreting data from educational systems to improve student learning outcomes. They use techniques from data mining, machine learning, and statistics to extract insights from large and complex data sets generated by students and teachers in educational settings. The focus is on understanding students' learning behaviors, motivation, and performance and using insights to inform educational policy and practice.

As instructors and educational technologists have greater access to data from online learning environments, there has been growing interest in using these data to support students (Van Horne et al., 2018). Two main research fields examine the use of educational data for understanding and even enhancing learning and teaching: LA and EDM. Some scholars propose LA and EDM to provide more insight into students' Collaborative Science Inquiry (CSI) in an Mobile Learning Environment (MLE) and to scale up teacher orchestration practices that use educational data. This section will discuss how LA and EDM methodologies are used to support orchestration.

LA has emerged as a powerful approach for investigating and understanding the CSI learning process. LA involves the collection, analysis, and interpretation of educational data to gain insight into learners' behaviors, interactions, and performance (Siemens et al., 2011).

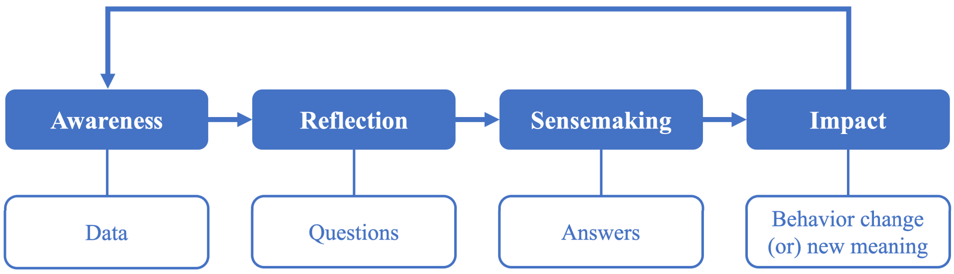
> LA uses dynamic information about learners and learning environments, assessing, eliciting, and analyzing it, for the real-time modeling, prediction, and optimization of learning processes, learning environments, and educational decision making.(Ifenthaler & Widanapathirana, 2014, p. 222)

For students, LA tools can monitor their progress and performance in an MLE, providing feedback and guidance to boost their inquiry skills and strategies. Displaying students' goals, plans, actions, results, and reflections in an MLE, along with comparisons to other groups or experts, allows students to identify gaps, strengths, and weaknesses in their inquiry process and receive suggestions for further actions or revisions (Kovanović et al., 2015; Looi et al., 2011). LA tools can also prompt students to engage in metacognitive activities, such as self-explanation, self-assessment, and peer feedback, promoting their understanding and awareness of their own and others' inquiry (Yilmaz & Yilmaz, 2020; Yılmaz, 2020).

By applying LA techniques, researchers and educators can also uncover valuable information about the dynamics of collaborative learning, identify patterns of engagement, and provide timely feedback and support to enhance the learning experience. One area of focus within LA research is the design and evaluation of LA dashboards. Verbert et al. (2013) raised the LA visualization (dashboard) process model to explain how teacher-facing LA dashboards help the application of educational data by instructors in four stages (See Figure 1). Specifically, by visualizing activity data in educational contexts, instructors can (1) have a better overview of the course, (2) identify questions that can help them improve their teaching, (3) understand the different learning statuses and styles of students, and (4) influence and find solutions for teaching behaviors (Verbert et al., 2013).

Figure 1

Visualization Processing Model by Verbert et al. (2013, p. 1501)



These dashboards serve as visual representations of the collected data, providing stakeholders, such as teachers, students, and researchers, with a comprehensive view of the collaborative learning process (Zhu & Wang, 2020). The visualizations and analytics offered by these dashboards enable stakeholders to monitor students' progress, identify areas of difficulty, and make informed decisions regarding instructional strategies and interventions (Han & Ellis, 2021; Zheng et al., 2021). Moreover, LA dashboards can facilitate adaptive support, allowing instructors to tailor their interventions to meet the specific needs of collaborative learning groups (Saleh et al., 2022).

The application of LA in CSI in an MLE extends beyond individual dashboards. Researchers have explored the use of LA to support class-wide interventions and peer feedback. For instance, Er et al. (2021) proposed a theory-oriented design that integrates collaborative peer feedback with LA to support class-wide interventions. Through the analysis of peer feedback interactions, instructors can gain insight into students' collaborative processes and identify opportunities for intervention and improvement.

Furthermore, LA techniques have been employed to analyze team interactions and group work evaluations. Zamecnik et al. (2022) investigated team interactions using LA dashboards and explored how visualizations and analytics influence collaboration processes. Their findings revealed that LA dashboards can enhance team awareness and foster productive collaborative behaviors. LA has also been utilized to identify multimodal behavioral profiles in collaborative learning activities. Nasir et al. (2021) employed LA to identify various profiles of collaborative learning in constructivist activities. By examining learners' behavioral patterns and interactions, researchers can gain a deeper understanding of the dynamics of collaborative science learning and design-targeted interventions.

Moreover, LA offers opportunities for studying metacognitive monitoring and inquiry-based learning in game-based environments. Taub and Azevedo (2018) utilized sequence mining techniques to analyze metacognitive monitoring and scientific inquiry during game-based learning. By analyzing learners' levels of efficiency and emotions, researchers can gain insights into the metacognitive processes involved in collaborative science learning.

Educational Data Mining (EDM) is a prominent data analysis strategy used to explore and uncover valuable insights from educational data in the context of Collaborative Science Inquiry (CSI) processes. EDM leverages computational methods, statistical techniques, and machine learning algorithms to analyze large-scale educational datasets and extract meaningful patterns, trends, and knowledge (Slater et al., 2017). By employing EDM techniques, researchers aim to gain deeper insights into the CSL process, identify factors influencing collaborative learning outcomes, and inform the design of effective interventions and instructional strategies.

Aldowah et al. (2019) conducted a comprehensive review and synthesis of EDM and LA in higher education. They highlighted the potential of EDM to support data-driven decision making in educational settings and emphasized its relevance to 21st-century higher education. The authors emphasized the importance of EDM in facilitating evidence-based practices and improving the quality of educational processes. In the CSI field, EDM techniques have been employed to investigate aspects of collaborative learning. For instance, Berland et al. (2014) applied EDM to explore the constructionist research approach in CSI. Through the analysis of data collected from collaborative learning environments, the researchers identified patterns of student engagement, interaction, and knowledge construction. The findings provided insights into the effectiveness of constructionist learning environments and contributed to the design of instructional strategies that promote collaborative learning.

G. W. Chen (2020) utilized EDM techniques to examine the factors influencing collaborative problem-solving awareness in science education. By analyzing data captured during collaborative problem-solving activities, the researchers identified significant predictors of awareness, including individual engagement, peer influence, and task complexity. These findings illuminate the dynamics of collaborative problem solving and inform the development of interventions to enhance students' awareness and collaboration skills.

Another relevant application of EDM to CSL is the analysis of collaborative peer feedback. Er et al. (2021) employed EDM techniques to design class-wide interventions for collaborative peer feedback. By analyzing peer feedback data, the researchers identified patterns of feedback provision, characteristics of effective feedback, and factors influencing the adoption of feedback. The insights gained from the EDM analysis facilitated the design of interventions aimed at improving the quality and effectiveness of collaborative peer feedback.

LA tools supported by EDM strategies have gained attention in the field of education. These tools aim to provide usable prediction models and visualization representations by synthesizing LA and EDM approaches (Xing et al., 2015).

Previous visualization designs of LA tools primarily relied on data-driven evidence, such as active time and login frequency, presented through basic bar or line charts. However, research suggests that such data-driven designs tend to be abstract and asynchronous, limiting their usefulness for just-in-time pedagogical actions (Schwendimann et al., 2017). The information provided by LA tools can also increase the cognitive load for teachers when interpreting data, given the constraints of time and knowledge (Aldowah et al., 2019).

To address these challenges, recent studies have focused on theory-oriented visualization strategies, aligning educational theories with interpreting students' learning processes (Pelánek, 2020). Theory-led design is an approach to developing LA tools that are based on first principles derived from theory (Kelly et al., 2015).

Theory-led design is based on the idea that theory can provide the first principles that guide the function, behavior, and structure of tools, which helps connect the design process explicitly to existing knowledge and generate new knowledge through tool use (Chatti et al., 2021). Theory-led design involves identifying relevant theoretical frameworks, deriving first principles from them, applying them to tool development, and evaluating and refining them through iterative cycles (Kelly et al., 2015). For example, van Leeuwen and Rummel (2019) designed and developed a theory-led dashboard to organize logged records as specific events with theoretical underpinnings, making the data more easily interpretable for practitioners.

Moreover, integrating constructionism with LA and EDM has shown potential for teaching complex content to novices. Constructionism (Vygotsky, 1978) is a learning theory that emphasizes students' creation of meaningful artifacts as a way of learning. EDM research can help constructionist researchers with LA guidance to investigate how students learn through making, and also pose new questions and challenges for them (Berland et al., 2014). By combining EDM and constructionism, researchers can gain more insights into the learning processes and outcomes of students, and advance the field of education (Baker et al., 2016).

However, the current design of EDM and LA visualization still lacks explicit guidance on teaching concerns (Schwendimann et al., 2017). The complexity of students' CSI learning in an MLE can present significant challenges for teachers' translating the results of LA into actionable interventions. Several studies have highlighted the following challenges in this regard:

1. Limited understanding of LA: Teachers may face challenges in interpreting and comprehending the data generated by LA tools (Nistor et al., 2018). They may lack the necessary knowledge and skills to effectively analyze and interpret data, hindering their ability to identify meaningful patterns and insights.
2. Translating data into actionable interventions: Even when teachers can access relevant data, they may struggle to translate data into meaningful actions to support students' learning (Er et al., 2021). Understanding how to leverage the insights provided by LA and design appropriate interventions based on such data can be a complex task.
3. Balancing group and individual needs: CSI involves individual and collaborative activities, challenging teachers to balance the needs of individual students and the group (Berland et al., 2015). LA may provide insights at the group and individual levels, requiring teachers to make informed decisions about when and how to intervene.
4. Addressing diverse student needs: In CSI, students can have diverse learning needs and preferences, requiring teachers to provide personalized support and interventions (Han & Ellis, 2021). LA can help identify these individual differences; however, teachers must have the skills and resources to implement tailored interventions effectively.
5. Time constraints and workload: Teachers already have a range of responsibilities and limited time available for planning and instruction (McKenney & Mor, 2015). Incorporating LA into their practice may require extra time and effort, which can be challenging to manage

within their existing workload.

6. Ethical considerations: The use of LA raises ethical concerns regarding student privacy, data protection, and informed consent (Romero & Ventura, 2020). Teachers must navigate these ethical considerations when collecting, analyzing, and using student data, which can add complexity to the facilitation of CSI.

2.4 Learning Analytics-Enhanced Teacher Orchestration

Learning Analytics (LA) can play a crucial role in teachers' orchestration practices by providing valuable insights into students' behavior, performance, and learning progress (Aldowah et al., 2019; Du et al., 2021; Koedinger et al., 2015).

Studies on LA-enhanced teacher orchestration were collected from three comprehensive databases for social science and educational research. They are the Education Resources Information Center (ERIC), Web of Science (WoS), and Elton B. Stephens Company (EBSCO). The literature search was limited to journal and conference papers published between 2010 and 2022. The search keyword is (teaching OR learning OR education) AND ("learning analytics" OR "educational data mining") AND (collaborative OR collaboration) AND (inquiry OR inquiry-based). The included articles contain technical descriptions and/or empirical evidence relating to the impacts/outcomes of applying educational data mining and/or learning analytics strategies for supporting teachers orchestrating collaborative science inquiry.

Some studies have explored the adoption of LA to address teachers' orchestration needs. Teachers can use the information provided by LA to monitor and intervene in students' learning and even the collaborative learning process (Ong et al., 2021). With the appropriate occasion, teachers' pedagogical moves and strategies can lead to leveraging impacts on students' learning (Bansal, 2018), which is also an orchestration objective. The LA feedback provided timely information on students' ideas and enabled teachers to intervene more effectively. We also found that the extended Initiation-Response-Feedback (IRF) was a helpful transitional talk pattern for instructing teachers to use LA feedback to guide whole-class discussions and elaborate on students' ideas. Extended (IRF) is a pattern of discussion between the teacher and learner in the classroom. The teacher initiates, the learner responds, and the teacher gives feedback. This approach has been criticized for being more about the learner saying what the teacher wants to hear than really communicating. This corroborates research on classroom discourse that recommends IRF to facilitate dialogue and the co-construction of knowledge among students (Mercer et al., 2009).

Because teachers are always concerned about students' agency, more research is needed to understand how these talk patterns can evolve into discourse in knowledge building classrooms. In addition, research is needed to understand how teachers interpret analytics tools, which affects how they use them (Wise & Schwarz, 2017). This study found that the teacher mainly used LA as a tool to help students learn curricular knowledge. Therefore, he focused the class discussion using LA to build on curricular keywords, such as "variable," to enhance students' science understanding. A limitation of this study was that students' collaborative inquiries were not captured from the face-to-face discussions in which they engaged while working on their own inquiry process.

LA-enhanced orchestration has been the subject of extensive research, as is evident in the literature reviewed. Du et al. (2021) conducted a meta-review, finding that most articles (69%)

targeted descriptive analytic results to support teaching and learning decisions, while the remaining articles aimed to provide feedback for teachers and learners. Decision support studies often utilized visualization techniques and text mining or presented statistical results directly. Dashboards were the preferred method for decision support, commonly including variables such as learning time and types of learning behaviors. Thresholds such as ranking, percentile, and course mean were employed to identify at-risk students. Feedback articles relied on descriptive analysis or predictive modeling to forecast learning performance or progress.

Instructors play a crucial role in LA and design according to Er et al. (2019). Their study emphasized the importance of close collaboration with instructors to identify target variables and practical constraints for prediction tasks. Although a learning design (LD)-specific predictive model did not outperform a generic model, LD-driven features were found to be influential. This comparison between instructors' perspectives and feature importance analysis helped identify issues in learning design and suggested improvements. Furthermore, Liang et al. (2022) highlighted the pedagogical implications of LA-enhanced group work orchestration, providing a low threshold for teachers to adapt workflows and utilize data-driven environments in classroom activities.

The literature reviewed also emphasized the support of teacher inquiry in students' collaborative learning. Mor et al. (2015) discussed learning design as a dual-natured activity, both creative and analytic, aiming to make teachers' intuitive processes visible and shareable. LA also supported collaborative inquiry; Ong et al. (2021) discovered that just-in-time feedback promoted diverse student ideas and enhanced teacher–student discussions. Teachers' interpretations of analytics tools played a crucial role in their use, highlighting the need for research. These findings collectively contribute to the understanding of LA-enhanced orchestration, emphasizing its potential for decision making, feedback provision, learning design improvement, and collaborative inquiry in educational contexts.

In recent years, LA has been adopted as a tool for enhancing teachers' orchestration of collaborative inquiry-based learning activities in a technology-rich classroom (Matuk et al., 2019; Tissenbaum & Slotta, 2019b; van Leeuwen et al., 2019; Yamada et al., 2019). Visualizing these LA tools creates conditions for the teacher to understand students' learning status, providing pedagogical guidelines for effective teacher orchestration in student collaboration (Prieto et al., 2019; Rummel, 2018; van Leeuwen & Rummel, 2019). LA can provide real-time information as evidence for teachers' orchestration to track and improve learners' involvement and performance (Amarasinghe et al., 2022). Please refer to Table 1 for a summary of 11 studies adopting LA to support teacher orchestration of CSI.

For example, discourse analysis visualization for instruction is based on the community of inquiry framework (Yamada et al., 2019). The visualization uses graphic elements to demonstrate and evaluate the expected outcomes from social interactions among group members. Nevertheless, using visualization, it is still challenging for teachers to predict what students will do next for just-in-time pedagogical actions. Another recent LA tool is a dashboard with real-time feedback, which is based on the knowledge community of inquiry theory (Tissenbaum & Slotta, 2019a, 2019b). The dashboard enables the teacher to be aware of students' task completion status, monitor the progress of activities, and decide if it is necessary to release the next task to the classroom. However, the dashboard only provides information to guide teachers in regulating students' learning through a prescribed, inflexible learning trail.

Table 1

Summary of 11 Studies Adopting Learning Analytics to Support Teachers' Orchestration of Collaborative Science Inquiry

#	Study	Tool name	Target	Theory	Collected data	Interactive features for orchestration
1	(Amarasinghe et al., 2022)	PyramidApp	University	CSCL	Student participation, answers, chat messages, and post-activity questionnaires	Adjusting activity timing: This includes increasing time for the current pyramid level, pausing and resuming activities, skipping pyramid levels, or ending activities.
2	(Kasepalu et al., 2022)	CoTrack	Upper secondary	N/A	Audio and log data	Monitoring speaking metrics: This refers to tracking each student's speaking time and turn count to ensure balanced participation.
3	(Bao et al., 2021)	KBSD[1]	University	CSCL	Knowledge elaboration, behavioral patterns, and social interaction	Selecting courses and viewing indicators: This allows teachers to choose a course and view specific group or individual student indicators via a dashboard.

Continued on the next page

Table 1

Summary of 11 studies adopting LA to support teacher's CSI orchestration (cont.).

#	Study	Tool name	Target	Theory	Collected data	Interactive features for orchestration
4	(Zheng et al., 2021)	HOWARD[2]	University	Self-regulated learning	Video and think-aloud data	Analyzing group dynamics: Group tags, social network analysis, task progress view, and activity view give insights into students' interactions and progress.
5	(Michos & Hernandez-Leo, 2020)	Community analytics dashboard	N/A	CSCL	Online participation	Tracking online participation: Dashboards that show the extent of students' participation in online activities.
6	(Er et al., 2019)	An LD-specific model	Lower secondary	N/A	Student behaviors on Massive Open Online Course (MOOC)	Observing student activities: Features that provide information on students' sequence activities, page-view activities, and active participation.

Continued on the next page

Table 1

Summary of 11 studies adopting LA to support teacher's CSI orchestration (cont.).

#	Study	Tool name	Target	Theory	Collected data	Interactive features for orchestration
7	(Holstein et al., 2019)	Lumilo	University	N/A	Futuristic classroom scenarios	Understanding student mindsets: Tools that allow teachers to see students' thought processes, identify students who are stuck, nudge students close to mastery, temporarily clone themselves, have enhanced oversight, detect misconceptions, and identify students prone to careless errors.
8	(Naranjo et al., 2019)	CloudTrail-Tracker	Primary & secondary	N/A	Percentage of completion	Reviewing progress dashboards: Dashboards showing the percentage of progress for each lab session and pending student actions.

Continued on the next page

Table 1

Summary of 11 studies adopting LA to support teacher's CSI orchestration (cont.).

#	Study	Tool name	Target	Theory	Collected data	Interactive features for orchestration
9	(Sergis et al., 2019)	TLAT[3]	Primary	Inquiry-based learning	Time spent and access pattern coherence	Evaluating guidance metrics: Information on the overall Consolidated Guidance Degree Index (CGDI) for the Inquiry-based Educational Designs (IED), specific missed guidance instances, and the cardinality of guidance instances in each inquiry phase.
10	(Viilo et al., 2018)	Knowledge forum	University	Collaborative inquiry learning	Student notes	Following event chains: Tracking chains of events in collective episodes for a clear understanding of group dynamics and collaborative learning experiences.

Continued on the next page

Table 1

Summary of 11 studies adopting LA to support teacher's CSI orchestration (cont.).

#	Study	Tool name	Target	Theory	Collected data	Interactive features for orchestration
11	(van Leeuwen, 2015)	CT & PS[4]	University	CSCL	Chat topics and group progress	Facilitating discussions and monitoring group activity: Tools similar to the CT and PS allow teachers to guide discussions and monitor group activity levels.

[1]: KBSD: Knowledge–Behaviour–Social Dashboard

[2]: HOWARD: Helping Others With Augmentation and Reasoning Dashboard)

[3]: TLAT: Teaching and Learning Analytics Tool

[4]: CT & PS: The Concept Trail (CT) and Progress Statistics (PS)

2.5 Issues with Learning Analytics Tool Implementation in Teacher Orchestration

In teacher orchestration, the implementation of Learning Analytics (LA) tools faces several challenges and gaps that must be addressed. This section discusses the key issues encountered when utilizing LA tools for orchestration and emphasizes the importance of resolving these challenges for successful implementation.

2.5.1 Lack of Teacher Training and Support

A lack of teacher training and support is a significant barrier to the effective implementation of LA tools for orchestration purposes (Du et al., 2021; Koedinger et al., 2015; McKenney & Mor, 2015). Many teachers may not be familiar with the use of LA tools or may lack the necessary training to utilize them effectively in the classroom. To enable teachers to leverage LA tools for orchestration, it is crucial to provide adequate training and support to ensure that they are equipped with the necessary knowledge and skills.

2.5.2 Limited Integration with Existing Instructional Practices

The limited integration of LA tools with existing instructional practices poses a challenge for their seamless adoption for orchestration (Bao et al., 2021; Hernandez-Lara et al., 2019; van Leeuwen, 2015). LA tools often struggle to integrate smoothly with established practices and technologies, leading to inefficiencies and difficulties in their utilization for orchestration. To address this issue, it is essential to develop LA tools that can seamlessly integrate with existing instructional practices and technologies, facilitating a smooth transition and effective utilization.

2.5.3 Privacy and Ethical Concerns

Privacy and ethical concerns are critical considerations for implementing LA tools for orchestration (Er et al., 2021; Romero & Ventura, 2020; Worsley & Blikstein, 2014). The collection, storage, and use of student data raise privacy and ethical concerns that must be carefully addressed. Teachers and educational institutions must protect student privacy and adhere to ethical guidelines when utilizing LA tools for orchestration.

2.5.4 Limited Customization and Adaptability

The limited customization and adaptability of LA tools pose challenges for meeting the diverse needs of teachers and students in various educational contexts (Amarasinghe et al., 2022; Han & Ellis, 2021; Wen & Song, 2021). LA tools often lack the necessary flexibility and customization options, restricting their usefulness for orchestration. To optimize the use of LA tools in orchestration, it is crucial to develop tools that can be customized and adapted to different educational contexts, allowing teachers to tailor them to their specific needs and requirements.

2.5.5 Data Interpretation and Actionability

Interpreting the data generated by LA tools and transforming them into actionable insights is another issue in orchestration practice (G. W. Chen, 2020; Liang et al., 2022; Rosé & Järvelä, 2021). While LA tools generate vast amounts of data, teachers may face challenges in interpreting the data and making actionable decisions based on it. Therefore, there is a need for improved data interpretation support and actionable insights to empower teachers to effectively utilize LA tools for orchestration.

2.5.6 Capturing Complex Aspects of the Learning Process

LA tools often focus on capturing quantitative data and may not fully encompass the complex and nuanced aspects of the learning process (Guo & Barmaki, 2020; Nasir et al., 2021; Saleh et al., 2022). This incomplete understanding of learning processes can limit the effectiveness of LA tools in supporting orchestration. To enhance the utility of LA tools in orchestration, it is crucial to develop tools that can capture both quantitative and qualitative data, providing a more comprehensive understanding of the learning process and enabling effective orchestration.

2.6 Summary of Research Gaps

Several research gaps identified in the literature review are summarized below.

1. Teachers are confronted with challenges and lack the capacity to manage Collaborative Science Inquiry (CSI) in a Mobile Learning Environment (MLE) both inside and outside the classroom;
2. Teacher orchestration with technology has been introduced to help teachers deal with the complex factors involved in CSI across social levels and learning spaces. However, most tools for teacher orchestration have been used in the classroom. Moreover, the key factors contributing to the successful teacher orchestration of CSI—"awareness, continuity, and flexibility"—conducted in an MLE have barely been addressed;
3. In recent years, Learning Analytics (LA) tools have been employed to support teacher

orchestration. However, these LA tools tend to be data driven. Even though some LA tools are designed with theoretical underpinnings, the visualization of these tools only provides information for teachers' pedagogical decision making regarding CSI learning activities in a linear way, step by step, without flexibility for just-in-time intervention;

4. Most LA tools for teacher orchestration have been adopted in secondary schools or tertiary education; and

5. A lack of communication among teachers and other stakeholders has prevented the effective implementation of LA tools for orchestration in practice.

In the light of the aforementioned issues to be explored and addressed, this thesis intends to develop and implement a theory-led LA tool on the m-Orchestrate app for teacher orchestration of CSI in an MLE in Hong Kong's primary schools, adopting Design-Based Research (DBR) to co-design the LA tool with teachers to address their real-time orchestration needs for awareness, continuity, and flexibility (Cao & Song, 2019). The m-Orchestrate app will be introduced in the next chapter.

2.7 Research Questions

Three research questions were addressed in this study:

RQ1: What were the affordances of the Learning Analytics (LA) tool for theory-led and interactive design for the teacher orchestration of Collaborative Science Inquiry (CSI) in a Mobile Learning Environment (MLE)?

RQ2: What was the impact of the theory-led LA tool on teachers' orchestration of CSI in an MLE?

RQ3: What was the impact of teacher orchestration supported by the theory-led LA tool on students' CSI performance in an MLE?

Chapter 3: Research Methodology: Design-Based Research

Design-Based Research (DBR) (Collins et al., 2004) is a systematic approach aimed at improving educational practices through iterative analysis, design, development, and implementation, based on collaboration among researchers and practitioners in real-world settings and leading to contextually sensitive design principles and theories (Barab & Squire, 2004; Rodríguez-Triana et al., 2015). Generally, DBR consists of 4 phases (Reeves, 2006) as follows: (1) the analysis of practical problems by researchers collaborating with practitioners, (2) the development of solutions informed by existing design principles and technological innovations, (3) iterative cycles of testing and refinement of solutions in practice, and (4) reflection to produce design principles and enhance the implementation of solutions.

DBR is a suitable approach for developing the Learning Analytics (LA) tool and exploring the impact of the LA tool because it tracks and records learning in the context of specific classrooms and courses (Reimann, 2016). It can help the researcher address problems with practical solutions and refine them to achieve better performance (Reeves, 2006). During the entire DBR process, problems, solutions, methods, and design principles can be refined at any time according to progressive findings. Thus, DBR was adopted for this proposed research to (1) develop, evaluate, refine, and improve the theory-led LA tool, (2) its impact on teacher orchestration in Collaborative Science Inquiry (CSI) in a Mobile Learning Environment (MLE), which in turn, influence students' performance in CSI, and (3) identify the design principles of the tool for teacher orchestration.

The four-stage DBR adopted in this study is presented in Figure 2 including (1) Phase I: Analysis of practical problems in orchestrating CSI in an MLE, (2) Phase II: The design and development of a theory-led LA tool, (3) Phase III: Iterative cycles of testing and refinement of the LA tool in practice, and (4) Phase IV: Reflection for further implementation of the LA tool.

Figure 2

Overview of the Four-Stage Design-Based Research Adopted in This Study

Phase I—Analysis of practical problems in orchestrating CSI in an MLE

Activity	Start	End	Duration
Trial use of the m-Orchestrate web platform and analysis of issues and needs for teacher orchestration	Nov. 2019	Dec. 2019	1 month
Development of the m-Orchestrate app	Dec. 2019	Jun. 2020	7 months

Phase II—Design and development of a theory-led LA tool

Activity	Start	End	Duration
Design and development of the LA tool	Jun. 2020	Jan. 2021	6 months
Debug and usability test of the LA tool	Jan. 2021	Mar. 2021	2 months

Phase III—Iterative cycles of testing and refining the LA tool in practice

Activity	Start	End	Duration
Cycle 1: Implementation of the LA tool with interactive features for just-in-time orchestration	Mar. 2021	May 2021	2 months
Cycle 2: Refinement and implementation of the LA tool with bupaR for orchestration practice	May 2021	Nov. 2021	6 months
Cycle 3: Implementation of the LA tool with pyBKT for orchestration practice	Nov. 2021	May 2022	6 months

Phase IV—Reflection for further implementation of the LA tool

Activity	Start	End	Duration
Reflection for further implementation of the LA tool	May 2022	Nov. 2022	6 months

3.1 Phase I—Analysis of Practical Problems in Orchestrating CSI in an MLE

In this phase, LA tool's needs and difficulties were recognized via collaboration with teachers. This phase involved two research activities: (1) a pilot study of trial use of the m-Orchestrate web platform was conducted, and issues and needs regarding teacher orchestration for Collaborative Science Inquiry (CSI) were identified; and (2) based on these issues and needs, the m-Orchestrate app was redesigned and developed based on the m-Orchestrate web platform for teacher orchestration.

3.1.1 Participants

Convenience sampling was adopted in this study. Four teachers with their four classes of Grade 4 (about 100) students from one primary school in Hong Kong participated in a pilot study in Phase I.

3.1.2 Subjects

The subjects of data collection in this phase were the science classes taught by the participating teachers. The focus was on implementing CSI activities related to the recycling theme and the experiences of both teachers and students during these lessons.

3.1.3 Data Collection

Data collection included teacher interviews, focusing on their experiences using the m-Orchestrate web platform and the practical problems they encountered in orchestrating CSI.

The interviews explored the difficulties faced by teachers and the suggestions for platform improvements for an MLE. The interview questions include “What do you think is most difficult in managing student collaborative learning conducted on mobile devices?” and “What do you expect to know about students’ collaborative learning status and how to deliver interventions according to their needs?”

3.1.4 Data Analysis

The collected data underwent inductive thematic analysis (Braun & Clarke, 2006; Guest et al., 2012). Teachers’ interviews were analyzed to identify the practical problems they faced in orchestrating CSI in an MLE and to uncover areas for improvement on the m-Orchestrate web platform by upgrading the m-Orchestrate from a web platform to an app. The analysis aimed to gain insights into the challenges teachers encountered and to inform the refinement of the LA tool for better teacher orchestration of CSI activities. The data analysis findings provided valuable input for subsequent phases of the study.

3.2 Phase II—Design and Development of a Theory-Led Learning Analytics Tool

This phase involved the design and development of a theory-led Learning Analytics (LA) tool on the m-Orchestrate app for teacher orchestration of Collaborative Science Inquiry (CSI) in an Mobile Learning Environment (MLE). The process consisted of three steps: First, a prototype of the LA tool was co-designed with preservice teachers who participated in Phase I, based on their feedback and suggestions. The co-design aimed to address the research questions and objectives of this study. Second, the system framework of the LA tool was drafted and negotiated with the developers on the research team, who were responsible for implementing the technical features and functions of the tool. The system framework specified the requirements, specifications, and design principles of the LA tool. Third, a theory-led LA tool was developed on the m-Orchestrate app, following the system framework and the co-design prototype. A usability test was conducted with a small group of preservice teachers to evaluate the functionality and usability of the LA tool and to identify any technical issues or bugs.

A Design-Based Research (DBR) approach was adopted to develop and evaluate the LA, whereby researchers, teachers, technicians, and pupils work in partnership. This is a progressive refinement approach to design (Barab & Squire, 2004; Collins et al., 2004; Sandoval & Bell, 2004). The rapid application development (RAD) method was adopted to develop a prototype that will evolve into a complete system design that provides affordances for teacher orchestration in terms of flexibility, continuity, and awareness. Three cycles of usability tests were conducted to refine the system. The outcomes of each trial use and usability test were used to make recommendations for refining the design and development of the m-Orchestrate system. Four teachers with their four Grade 4 classes were involved at this stage. In this phase, the focus shifted to conducting usability testing of the m-Orchestrate web platform with two pre-service teachers. The aim was to evaluate the usability and user experience of the LA tool in the context of teachers' orchestration of CSI activities.

3.2.1 Participants

Convenience sampling was adopted in this study. Two pre-service teachers with their two Grade 4 classes of (about 50) students from a local primary school in Hong Kong participated in a usability test in Phase II. They were actively involved in the usability testing of the m-Orchestrate web platform and provided feedback on its usability and functionality.

3.2.2 Subjects

The subjects of the usability testing were CSI activities related to the recycling theme that was orchestrated by the two pre-service teachers with their students using the m-Orchestrate web platform. These activities were conducted in a controlled setting, allowing the evaluation of the LA tool's usability.

3.2.3 Data Collection

Data were collected through qualitative research methods, including observation of pre-service teachers' and students' interactions with the m-Orchestrate web platform during CSI activities, and post-task interview to gather their feedback and perceptions and collect qualitative data on the usability issues encountered.

3.2.4 Data Analysis

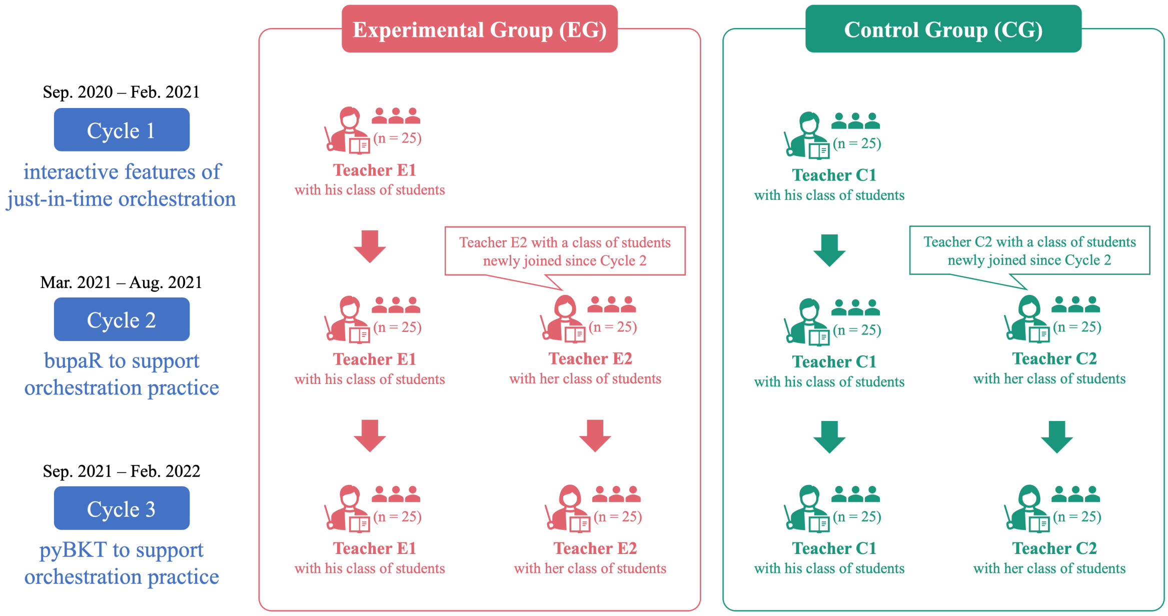
The collected data underwent inductive thematic analysis (Braun & Clarke, 2006; Guest et al., 2012) to identify usability issues, user satisfaction, and suggestions for improvement. The analysis focused on pre-service teachers' and their students' feedback and observations during their interactions with the m-Orchestrate web platform. The findings from the analysis were used to refine the design and functionality of the LA tool, ensuring its usability and effectiveness in supporting teachers' orchestration of CSI activities.

3.3 Phase III—Iterative Cycles of Testing and Refining the Learning Analytics Tool in Practice

The proposed Design-Based Research (DBR) consists of three cycles to investigate, refine, and implement the use of the Learning Analytics (LA) tool on the m-Orchestrate app: (1) implementation of the LA tool with interactive features for just-in-time orchestration, (2) refinement and implementation of the LA tool supported by Business Process Analytics in R (bupaR) (Janssenswillen et al., 2019) to support orchestration practice, and (3) refinement and implementation of the LA tool supported by Python implementation of the Bayesian Knowledge Tracing (pyBKT) (Anirudhan et al., 2021) to support orchestration practice. bupaR is an R package commonly adopted for process analysis of log data. It obtains the potential to support orchestration practices by providing insights into students' Collaborative Science Inquiry (CSI) learning process. pyBKT was commonly used for modeling and predicting highly-related learners' knowledge and skills, which is feasible to be revised to address further concerns during teacher orchestration of CSI in an Mobile Learning Environment (MLE) (i.e. highly-related inquiry activities and completion status of inquiry phases). Figure 3 presents the participants and research activities in the three iterative cycles.

Figure 3

Participants and Focus of the Three Iterative Cycles in Phase III



3.3.1 Participants

Convenience sampling was adopted in this study. Four teachers with their four Grade 4 classes of (about 100) students from two local primary schools in Hong Kong participated in Phase III. The researcher communicated closely with four teachers from the General Studies panel to implement the m-Orchestrate app on the subject of General Studies (the core subject for science education) in Hong Kong primary schools. The teachers and their students had already learned how to use the m-Orchestrate web platform and were invited to participate in the proposed research by convenience sampling. Their schools provided mobile devices and wireless networks for students on campus. The participating teachers had experience in teaching general studies for at least three years and were interested in practicing pedagogical innovation.

3.3.2 Subject

The general studies subject is the core subject of science education in Hong Kong's primary schools. During the proposed research period, the teachers took two classes in Grade 4. Thus, three units with science-related topics in this grade were adopted. These are as follows: (1) Eight Planets in the Solar System, (2) Plants, and (3) Force, Motion, and Simple Machines.

3.3.3 Data Collection

This section describes the data collection methods used to address the three RQs in each iterative cycle of Phase III. The RQs are related to the affordances, impact, and design of a LA tool that supports teachers' orchestration of students' CSI learning in an MLE.

RQ1: What were the affordances of the LA tool for theory-led and interactive design for the teacher orchestration of CSI?

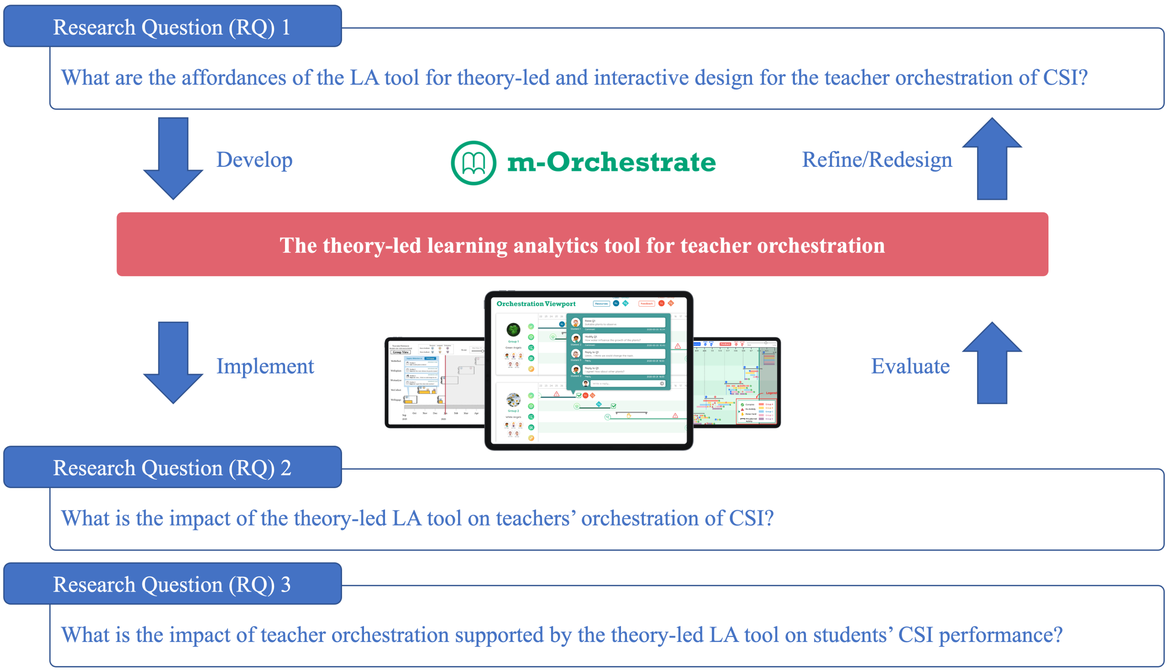
RQ2: What was the impact of the theory-led LA tool on teachers' orchestration of CSI?

RQ3: What was the impact of teacher orchestration supported by the theory-led LA tool on students' CSI performance?

The DBR process in this study involved three cycles of design, enactment, analysis, and refinement of the theory-led LA tool for teacher orchestration of CSI in an MLE. The three RQs guided the exploration of the design and impact of the LA tool in each cycle. Figure 4) summarizes how the LA tool was redesigned and refined based on the findings from each RQ.

Figure 4

Research Questions in Each Cycle



RQ1 explored the affordances of the LA tool for theory-led and interactive design for teacher orchestration of CSI. The affordances refer to the possibilities and opportunities that the LA tool offers for teacher orchestration of CSI, based on a theoretical foundation that informs the principles, methods, and tools needed to facilitate CSI in an MLE. The findings from RQ1 helped identify the design features and functionality of the LA tool that can support teacher orchestration of CSI in an MLE.

RQ2 investigated the impact of the theory-led LA tool on teachers' orchestration practices in facilitating CSI. The impact refers to the effects and outcomes that the LA tool has on teachers' orchestration practices and decisions, based on a framework that explores how digital tools and LA can assist teacher orchestration practices in CSI. The findings from RQ2 helped evaluate how the LA tool enhances teachers' orchestration practices in CSI by providing data and insights into students' performance, and how teachers can monitor, evaluate, and adjust their orchestration practices based on the data and insights from the LA tool.

RQ3 evaluated the impact of teacher orchestration supported by the theory-led LA tool on students' CSI performance. The impact refers to the effects and outcomes that teacher orchestration has on students' learning outcomes, based on data from the LA tool that tracks and evaluates student progress in real time. The findings from RQ3 helped measure how teacher orchestration supported by the LA tool enhances students' performance in CSI by providing feedback and guidance to students, and how student engagement, performance, and feedback can be improved by teacher orchestration supported by the LA tool.

The data were collected from three iterative cycles in Phase III of the DBR, in which teachers and students participated in CSI activities using the LA tool. The data included log data from the LA tool and the m-Orchestrate app, teacher interviews, and students' pre- and post-quizzes. The following subsections provide more details about each data source. The following data were collected during each implementation cycle to address the RQs (refer to Table 2).

Table 2

Data Collection in the Three Iterative Cycles of Phase III

#	Data Collection	Research Question (RQ)		
		RQ1	RQ2	RQ3
(1)	Teacher operation records on the LA tool	✓		
(2)	Semi-structured teacher interviews	✓	✓	
(3)	Student domain knowledge on pre- and post-quizzes			✓

3.3.3.1 Teacher Operation Records on the Learning Analytics Tool. The log data of teaching behaviors on the m-Orchestrate app and the LA tool were analyzed to identify when and how teachers orchestrate CSI learning activities using the LA tool. The data logged in the m-Orchestrate app included the precise content that teachers released to targeted students. The data logged in the LA tool contained (1) when teachers recognized what students needed, (2) when, where, how, and what resources and feedback teachers released to students, and (3) when teachers viewed advanced data analysis results in the LA tool developed in the DBR. There were comments on inquiry questions in the WeEngage phase, resources, and feedback on different social levels and activities among all phases.

3.3.3.2 Semi-Structured Teacher Interview. Semi-structured teacher interviews were conducted after each cycle to determine teachers' perceptions of and experience with using the LA tool to orchestrate CSI. The interviews were audiotaped and conducted in English.

3.3.3.3 Student Domain Knowledge Pre- and Post-Quizzes. Students' scores on pre-quizzes and post-quizzes were collected to examine (1) their inquiry skills (e.g., hypothesis generation, planning investigation, analysis, and interpretation) (Bell et al., 2010) and (2) their understanding of scientific knowledge. The researcher designed the test and negotiated with the participating teachers to match their learning content and objectives.

3.3.4 Data Analysis

This section describes the data analysis methods used to address the three RQs in each iterative cycle of Phase III. The RQs were related to the affordances of the LA tool, and its impact on teacher orchestration of students' CSI learning in an MLE, which in turn, impacted students' learning outcomes. The data analysis methods included (1) bupaR analysis, (2) inductive thematic analysis, and (3) independent and paired-sample t-tests. The following subsections provide more details about each data analysis method.

3.3.4.1 Business Process Analytics in R (bupaR) Analysis of Operation Records on the LA Tool. The bupaR (Janssenswillen et al., 2019) analysis is a process mining technique that can extract and analyze information from event logs. bupaR can filter, mutate, arrange, group, and join event logs based on various criteria such as activity, resource, case, or time. It can also create graphical representations of event logs like process maps and matrixes. Therefore, bupaR is useful for identifying the key and different features in the process of teacher orchestration. An "event log" is a record of the activities performed by the actors (e.g., teachers) in a system (e.g., LA tool) over time.

By applying bupaR analysis, we could generate process maps and a process matrix that showed the sequences and frequencies of teachers' operation records of the primary features of the LA tool (see R source codes in Appendix A). These features included a dashboard, timeline, heatmap, network, and feedback. The process maps and process matrix could help us understand how teachers interacted with the LA tool in each cycle and how their interactions changed over time. We could also compare teachers' interactions across cycles, groups, and contexts. The results of the bupaR analysis could provide insights into teachers' adoption, usage, and perception of the LA tool, as well as their pedagogical strategies and challenges in facilitating students' CSI learning in an MLE. The results could also inform the design and improvement of the LA tool and its features for future iterations.

3.3.4.2 Inductive Thematic Analysis of Teacher Interview. To analyze transcripts from online semi-structured in-depth interviews with teachers utilizing an LA tool, this research employed an inductive thematic analysis approach (Braun & Clarke, 2006). This data-driven method involves a comprehensive examination of data without relying on a predetermined coding framework (Guest et al., 2012). In this process, the transcripts were meticulously read and categorized into themes and concepts, allowing the observation of data patterns and the interpretation of emerging insights. These patterns are typically clustered and termed "codes."

The use of inductive thematic analysis (Braun & Clarke, 2006; Guest et al., 2012) was appropriate for this research, as it aimed to explore the perceptions and opinions of teachers. Consequently, a careful re-examination of the data and identification of emerging themes across transcripts were essential for addressing the research questions. The flexibility of the inductive thematic analysis was advantageous in this context (Joffe, 2011). This adaptability enabled the researcher to emphasize valuable and intriguing concepts during the analytic process. However, flexibility was also a disadvantage, as it was challenging to determine which themes to include or exclude. Terry et al. (2017) argued that the versatility of inductive thematic analysis could lead to ambiguous interpretations due to the lack of structure in the analytic process.

To address the unstructured analysis issue associated with inductive thematic analysis, the following procedure was implemented during the data analysis stage: (1) reading transcripts and noting themes/concepts, (2) re-reading transcripts and noting additional themes/concepts, (3) drafting themes and codes, (4) defining themes and codes and reviewing transcripts to develop further themes and codes, (5) observing patterns among themes and codes, (6) reviewing transcripts one last time to finalize themes and codes, and (7) concluding the analysis.

3.3.4.3 Independent and Paired-Sample T-Tests of Student Domain Knowledge Pre- and Post-Quizzes. To examine the effects of the developed and refined LA tools on students' learning outcomes, the study conducted independent and paired-sample t-tests on the scores of students' pre- and post-quizzes in each cycle. This study adopted a DBR approach with many cycles of intervention and evaluation. In each cycle, the researcher developed or refined the LA tool based on teachers' and students' feedback and needs and implemented it in real classroom settings. The study measures the effects of the LA tool on students' learning outcomes by comparing their scores on quizzes before and after the intervention. The quizzes were designed to assess students' understanding of the course content and inquiry skills. The study used individual and paired-sample t-tests to compare the mean scores of the pre- and post-quizzes for each cycle using the SPSS software, a statistical tool for data analysis.

3.3.5 Research Activities in Each Cycle

This section presents research activities in each iterative cycle in Phase III of the DBR. They are (1) design/redesign, (2) development, (3) implementation, and (4) refinement stages. Each cycle had the same activities but different foci.

3.3.5.1 Design/Redesign. Based on the findings and proposed refinements identified from a previous cycle/phase, the design/redesign established a new framework of the LA tool to extend its capabilities with further features to support focused orchestration principles in terms of awareness, continuity, and flexibility in the coming development stage. The proposed solutions and approaches were designed and negotiated with participating teachers collaboratively.

3.3.5.2 Development. Based on the design and redesign confirmed in the previous stage, the LA tool was further developed according to the refined design to compile with target teacher orchestration needs.

3.3.5.3 Implementation. This stage aimed to implement the refined LA tool for teacher orchestration principles to investigate the affordances of the LA tool and their impacts on teacher orchestration practices and students' CSI learning performance.

3.3.5.4 Refinement. Some limitations and further issues were found from the implementation stage of the LA tool. Features of the LA tool that could be improved in the next cycle or in the future were expected.

3.4 Phase IV—Reflection for further Implementation of the Learning Analytics Tool

The final phase of the Design-Based Research (DBR) involved synthesizing the design principles and research notes of the Learning Analytics (LA)-enhanced orchestration tool that emerged from the previous phases. The design principles were derived from the analysis of the data collected from the teachers and students who used the tool in authentic classroom settings. They reflected the pedagogical and technical aspects of the tool that supported the effective orchestration of collaborative learning with LA.

The research notes documented the methodological decisions and challenges of conducting DBR in complex and dynamic educational contexts. They provided insights and recommendations for future researchers who aimed to design, develop, and implement LA tools in similar settings. The major findings from the entire DBR process were summarized and illustrated in this phase, highlighting the main contributions and implications of the study for theory and practice.

Chapter 4: Implementation and Results of Design-Based Research

This chapter reports on the implementation and results of Design-Based Research (DBR). Each phase's research activities and progressive findings are covered in separate subsections. The entire DBR lasted for three years with four phases presented in Table 3. This thesis adopts DBR to (1) identify the needs of teachers' orchestration of Collaborative Science Inquiry (CSI) in an Mobile Learning Environment (MLE), (2) design and develop Learning Analytics (LA) solutions, (3) implement and refine these solutions, and (4) provide a theory-led and interactive LA tool as a deliverable artifact with design principles.

Table 3

Four Stages of the Design-based Research

Phase	N. of Participants		Time and Period		
	Teacher	Student	Start	End	Duration
Phase I: Analysis of practical problems in orchestrating collaborative science inquiry in a mobile learning environment	4	100	Mar. 2021	May 2021	2 months
Phase II: Design and development of a theory-led learning analytics tool	2	50	May 2021	Nov. 2021	6 months
Phase III: Iterative cycles of testing and refining the learning analytics tool in practice	4	100	Mar. 2021	May 2022	14 months
Phase IV: Reflection for further implementation of the learning analytics tool			May 2022	Nov. 2022	6 months

4.1 Phase I—Analysis of Practical Problems in Orchestrating Collaborative Science Inquiry in a Mobile Learning Environment

The purpose of this phase was to discuss and identify the feasibility of the web application of m-Orchestrate as an intervention for teacher orchestration in collaborative inquiry-based learning in science through the researcher-teacher partnership.

Table 4 demonstrates the research activities, time, and period of the study's Phase I. It has two main activities: the trial use of the m-Orchestrate web platform and the development of the m-Orchestrate app. The first activity in Table 4 presents the trial use of the m-Orchestrate web platform. This activity lasted from November 2019 to December 2019. Issues and needs were identified for teacher orchestration for Collaborative Science Inquiry (CSI) in an Mobile Learning Environment (MLE). In view of the issues and needs, the second activity presented in Table 4 focused on the development of the m-Orchestrate app for teacher orchestration. This activity started in January 2020 and ended in February 2021. The duration of this activity was three months.

Table 4

Research Activities in Phase I

Activity in Phase I	Time and period		
	Start	End	Duration
Trial use of the m-Orchestrate web platform and analysis of issues and needs for teacher orchestration	Nov. 2019	Nov. 2019	1 month
Development of the m-Orchestrate app	Dec. 2020	Feb. 2021	3 months

4.1.1 Introduction to the m-Orchestrate Web Platform

The m-Orchestrate web platform is an application that assists teachers and students with CSI. The system is powered by dynamic web pages, and it includes entities in the MySQL database (see Figure 5). The system design was published in a conference paper by Song et al. (2019). The app manipulated students' CSI through five phases of features: WeEngage, WeExplore, WeAnalyse, WeExplain, and WeReflect. From the user interface, users can view profile information (see Figure 6a), group information (see Figure 6b), activities in different inquiry phases (see Figure 6c), and multimedia resources, including data records, notes, and trails (see Figure 6d) (Song et al., 2019). The web application comprises two interfaces: One for students and one for teachers.

Figure 5

System Framework of the M-Orchestrate Web Platform

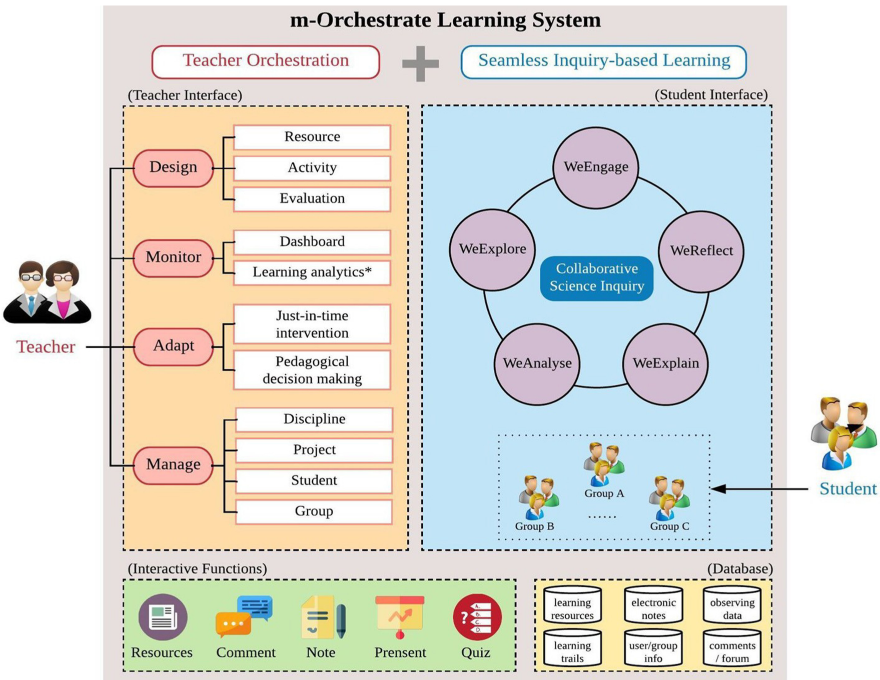


Figure 6

User Interface of the M-Orchestrate Web Platform

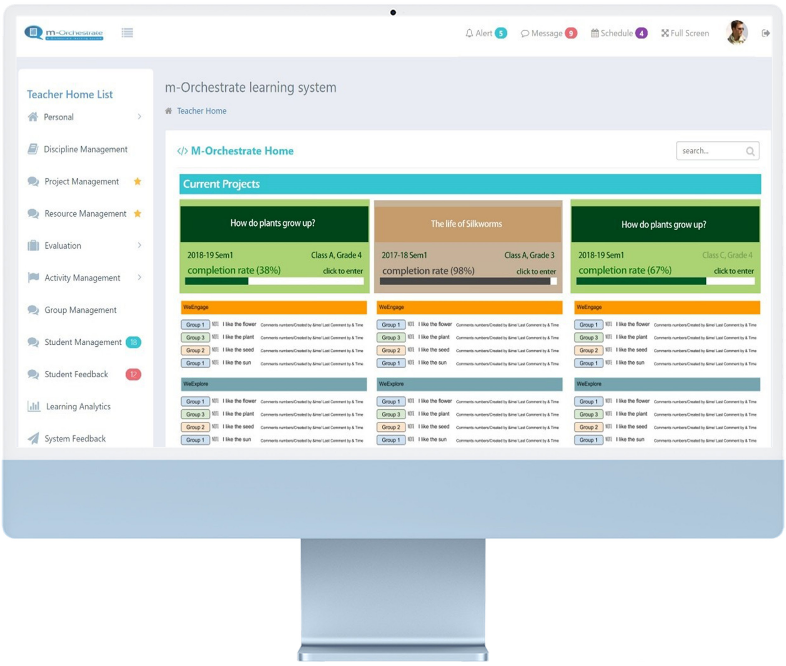
(a) (b) (c) (d)

The student's interface (see Figure 6) contains a menu with ongoing and completed projects. Within each project, the students work collaboratively in a separate space. The project's homepage illustrates the five phases of CSI, and students can move freely between phases. Each phase features a note-taking function in which students can post text, pictures, videos, drawings, and concept maps. There are also additional plugins with specific functions.

The teacher's interface (see Figure 7) is designed to facilitate teacher orchestration, enable teachers to design inquiry projects with learning tasks, monitor students' progress through the dashboard and LA, intervene and make pedagogical decisions in real time, and manage inquiry projects, including their status, contents, and student grouping records. The teacher's interface also allows direct commentary on forums or student notes.

Figure 7

Teacher Interface of the M-Orchestrate Web Platform



4.1.2 Pilot Study of Teacher Orchestration Using the M-Orchestrate Web Platform

In the pilot study, we focused on the feasibility of the web application in m-Orchestrate as an intervention for teacher orchestration and distilling and refining more teacher orchestration principles in collaborative inquiry-based learning in science.

The science learning topic was Recycling, which lasted two weeks with four teachers in two primary schools. Teaching plans were collected. Subsequently, we revised and returned them to the teachers. The lesson plans were shared, after which we communicated with teachers about plan updates, focusing on how to design lessons based on collaborative inquiry-based learning principles guided by the m-Orchestrate app. After discussing the teaching plans with the teachers, we enacted the lessons and trial use of the web version m-Orchestrate app.

During the implementation, we collected data regarding (1) class observation (see Figure 8a), (2) teacher and student interviews, (3) teaching plans (see Figure 8b), and (4) student artifacts (see Figure 8c and 8d).

Figure 8

Use of the M-Orchestrate Web Platform in Phase I

(a) Students working on the m-Orchestrate learning platform

(b) Discussion on an inquiry question "Can we recycle the drink cartons?"

(c) Dismantle empty drink cartons and study different layers (1)

(d) Dismantle empty drink cartons and study different layers (2)

4.1.3 Issues Identified from the Implementation of the m-Orchestrate Web Platform

4.1.3.1 System Infrastructure. The implementation of the m-Orchestrate web platform in two primary schools in Hong Kong revealed the limitations of the system's infrastructure. The current design of the system presented student activities in a purely descriptive manner, which limited the teacher's ability to identify potential issues and offer appropriate support. This descriptive presentation led to confusion and frustration among the teachers, who felt overwhelmed by the large volume of information on the platform. Furthermore, the system suffered from performance issues, including slow launching speed, asynchronous communication limitations, content collision or conflict, compatibility problems with devices and browsers, lack of support for weblink posting, inability to upload large-sized files, errors in analyzing data, and inadequate support for creating slide shows and collaborative mind maps. These limitations significantly hindered the attainment of learning objectives and the effective teacher orchestration of CSI.

To address these issues, the m-Orchestrate web platform was further developed into a mobile app that could be launched on the iOS and Android operating systems. This transition aimed to provide a more seamless user experience and eliminate the limitations of the web platform's system infrastructure.

4.1.3.2 Students' Needs: Specific Features of CSI Learning. From the students' perspectives, the adoption of the CSI model in the m-Orchestrate web platform received positive feedback. Students expressed the need for additional features to fulfill specific requirements in the five inquiry phases. They highlighted the importance of having a discussion space or forum (WeEngage) to raise and negotiate group inquiry activities. Additionally, a work division and data collection container (WeCollect) were deemed necessary for convenient collaboration. Direct analysis tools (WeAnalyse) were also desired as pipelines for analyzing collected data without manual downloading and uploading. Furthermore, the students emphasized the value of a slide show preparation tool (WeExplain) so they could select group artifacts and multimedia logs made in other phases. Finally, an interactive table (WeReflect) was perceived as a valuable toolkit to facilitate continuous reflection throughout the inquiry process. These desired features were considered essential for enhancing student engagement and improving the effectiveness of CSI learning.

4.1.3.3 Teachers' Needs: Insights and Scaffoldings for Orchestration. From the teachers' perspectives, further training was required to internalize collaborative inquiry-based learning approaches and effectively use the m-Orchestrate web platform to scaffold and orchestrate students' activities. To improve the system's effectiveness in supporting teachers' orchestration of CSI, the design should be updated to provide more in-depth analysis and feedback on student activities. This would enable teachers to identify potential issues and offer appropriate support.

The m-Orchestrate web platform has the potential to assist teachers in dealing with the complex factors involved in CSI across social levels and learning spaces. However, current tools for teacher orchestration have primarily been used in the classroom setting, and key factors, such as "awareness, continuity, and flexibility," required for successful teacher orchestration in an MLE have received limited attention.

To address these gaps, the incorporation of an orchestrating LA framework is recommended, leveraging the potential of LA tools to enhance teachers' orchestration. This approach, although not widely used in existing research, holds promise for effectively implementing LA tools and providing just-in-time interventions, thereby enhancing the teacher orchestration of CSI in an MLE.

Concerning the issues identified above, the m-Orchestrate web platform was designed to shift to a mobile application that can run directly on iOS and Android platforms and support advanced LA approaches with more specific features and clear log data schemes.

4.1.4 Introduction to the m-Orchestrate App

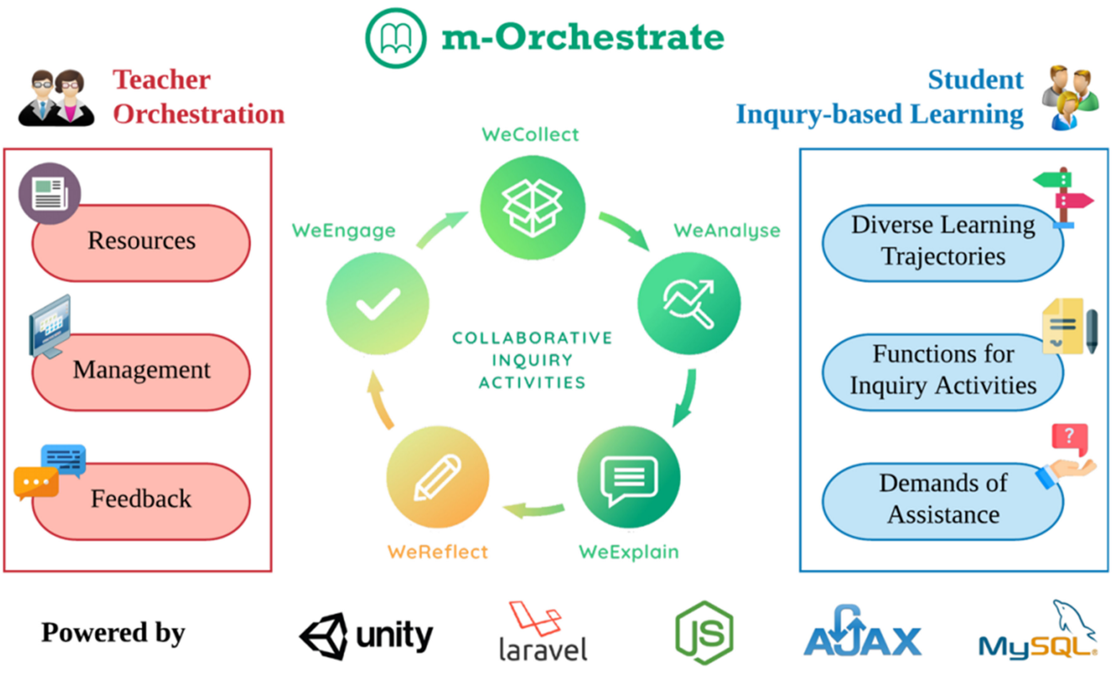
The m-Orchestrate app is a learning solution that supports teacher orchestration and student CSI in an MLE. The app integrates mobile technology into the science curriculum as well as assessment, collaboration, and inquiry-based pedagogy grounded in social constructivist theories.

The newly developed m-Orchestrate app as an iOS/Android application is an innovative tool designed to facilitate efficient group inquiries. The m-Orchestrate app is specially designed to support group-based inquiry initiatives using an inquiry cycle model comprising five phases: WeEngage, WeCollect, WeAnalyse, WeExplain, and WeReflect (see Figure 9).

With its intuitive and versatile features, this app provides a user-friendly interface that simplifies engaging, collecting, analyzing, explaining, and reflecting on inquiry processes. These phases are critical components of group-based inquiry processes as they enable group members to generate data from multiple sources and perspectives, analyze the data collected, and interpret the findings of their investigation through reflection, presentation, and collaboration. By utilizing the m-Orchestrate app, users can streamline and optimize their group-based inquiry processes for maximum efficacy, yielding deeper insights and richer outcomes.

Figure 9

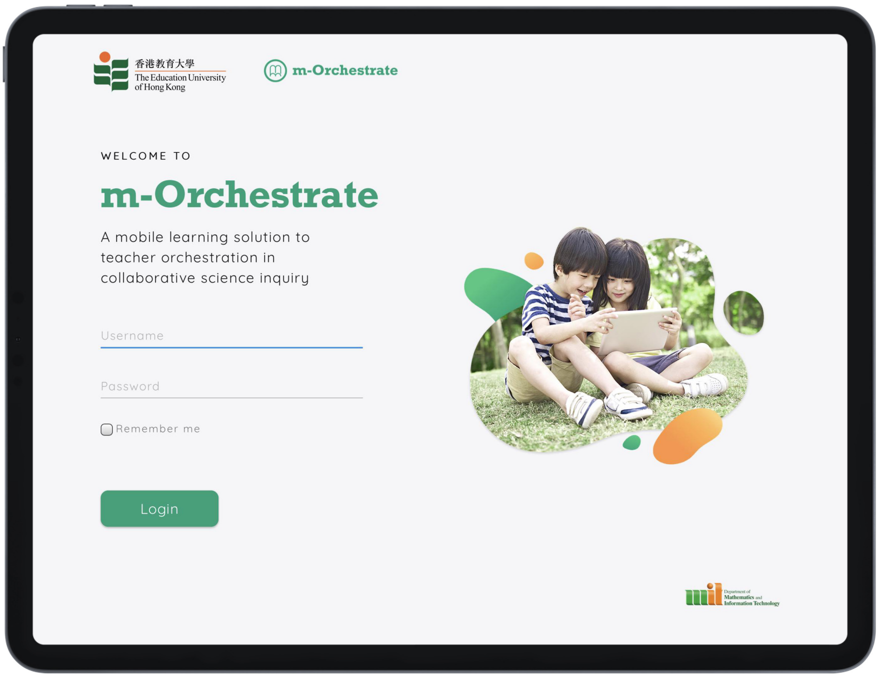
System Framework of the M-Orchestrate App



4.1.4.1 Login Page. The app has a simple user interface with varying elements and features. The user interface of the m-Orchestrate app is designed to be simple, intuitive, and user friendly. It allows users to easily access the app's functions and features and to engage in CSI in diverse contexts. For example, the welcome page of the m-Orchestrate app is shown in Figure 10. The app's name, m-Orchestrate, is displayed at the top center of the screen. Below the app's name are two buttons: "Login" and "Register." The "Login" button allows existing users to enter their username and password to access the app. The "Register" button allows new users to create an account by providing personal information and choosing a username and password.

Figure 10

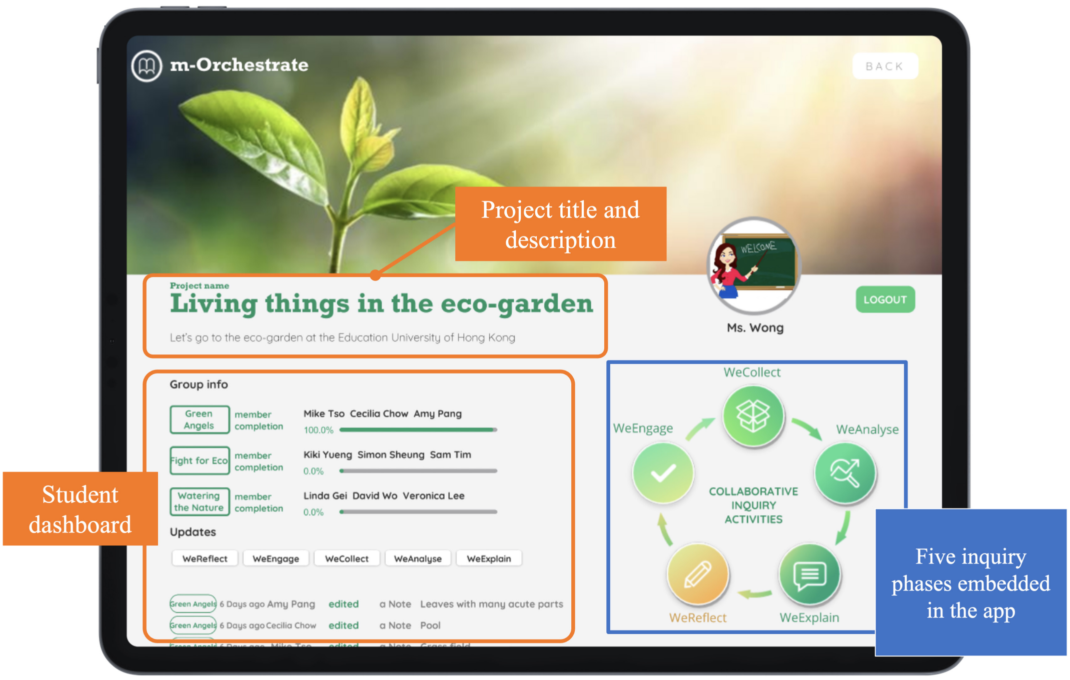
Login Interface of the M-Orchestrate App



4.1.4.2 Home Page. The project homepage interface of the app consists of (1) a header at the top, (2) a circular navigation bar at the bottom right, and (3) a student dashboard at the bottom left (see Figure 11). The header displays the app's logo, the project's name, and the username. Each phase has a distinct color and icon to indicate its function and purpose. The content area displays the activities of students from different groups posted in each phase. The content area also shows the group members and their roles in the project. The navigation bar allows the user to switch between inquiry phases: WeEngage, WeExplore, WeAnalyse, WeExplain, and WeReflect. These buttons correspond to specific features in the five phases of the inquiry-based learning model developed by the research team. The app allows students to visit, review, and modify phases iteratively without being restricted to a fixed inquiry sequence. The image shows the home page of the app, where students can see their group name, group members, group inquiry questions, and the five phases of the inquiry process. Each phase has its own color and icon to indicate its function and status. The app also reveals the teacher's name and avatar in the top right corner, indicating that the teacher can monitor and guide the student's progress.

Figure 11

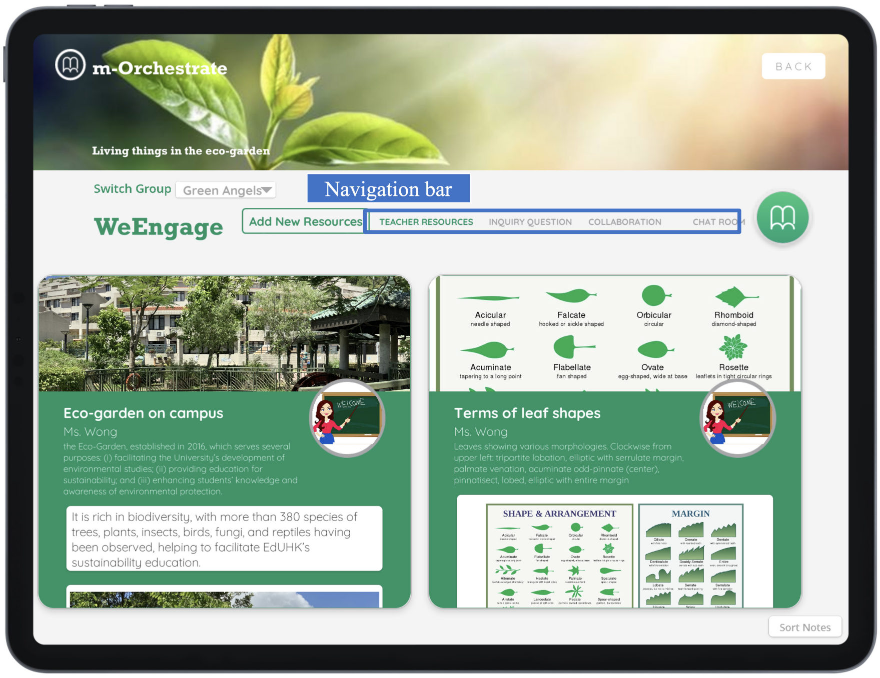
Homepage Interface of the M-Orchestrate App



4.1.4.3 WeEngage Phase. Figure 12 depicts the user interface of the m-Orchestrate app in the WeEngage phase. The WeEngage phase aims to help students brainstorm research problems, engage in pre-reflection, and raise group questions. The interface shows a teacher resource tag, which was captured from a teacher's account. The layout has three main parts: (1) the top navigation bar, which allows teachers to add teacher resources, view and comment on students' inquiry discussion, switch between phases, and access the group chat function; (2) the main content area, which reveals posted teacher resources in various forms, such as text, picture, and video; and (3) the bottom toolbar, which provides shortcuts for teachers to edit teacher resources, upload files from the device or the cloud, and make shortcuts for photos or videos with the camera/from albums of mobile devices, after which they can be dragged and dropped to rearrange their order.

Figure 12

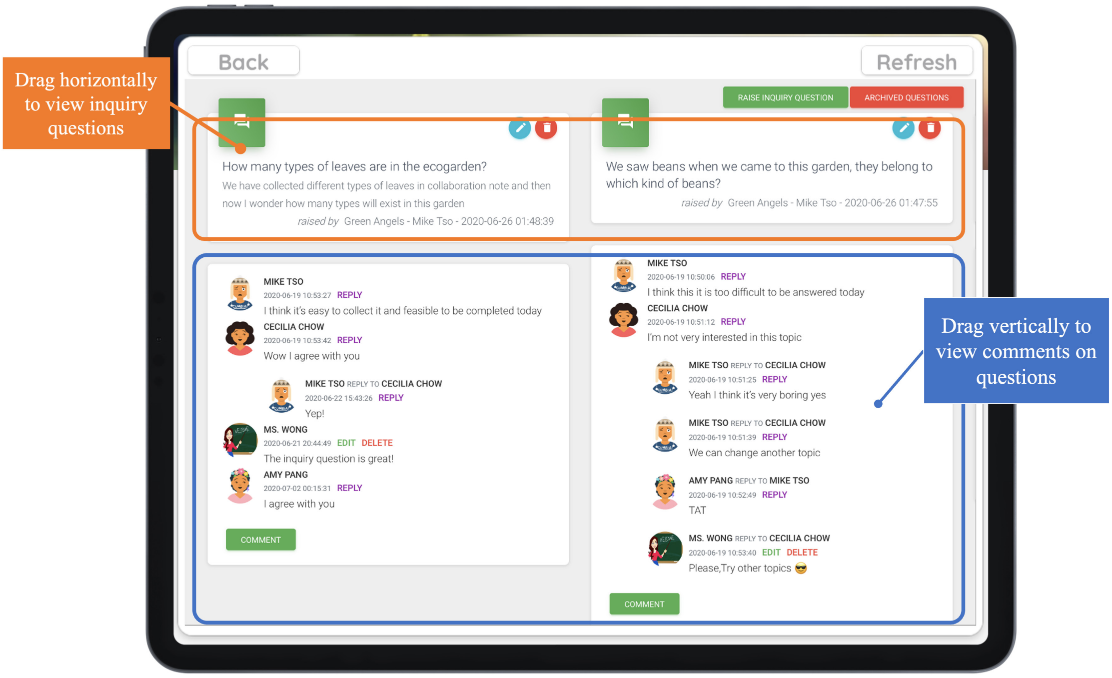
WeEngage Interface of the M-Orchestrate App



After entering the inquiry question, users can see the interface for students to raise and discuss inquiry questions in the WeEngage phase (see Figure 13). The interface of the m-Orchestrate app was designed to facilitate CSI and foster students' engagement and interest in learning science. It consists of two main parts: the navigation bar and the inquiry question board. The navigation bar can be used to create, modify, and delete inquiry questions. The inquiry question board in the middle displays the inquiry questions that each group member posted. Students can tap on the edit or delete buttons of a question to view or modify details. They can scroll horizontally to view other inquiry questions. They can also scroll vertically to view other comments on the questions. Students can send text messages with emojis to discuss their inquiry questions and share their ideas.

Figure 13

Raising Inquiry Questions in the WeEngage Phase

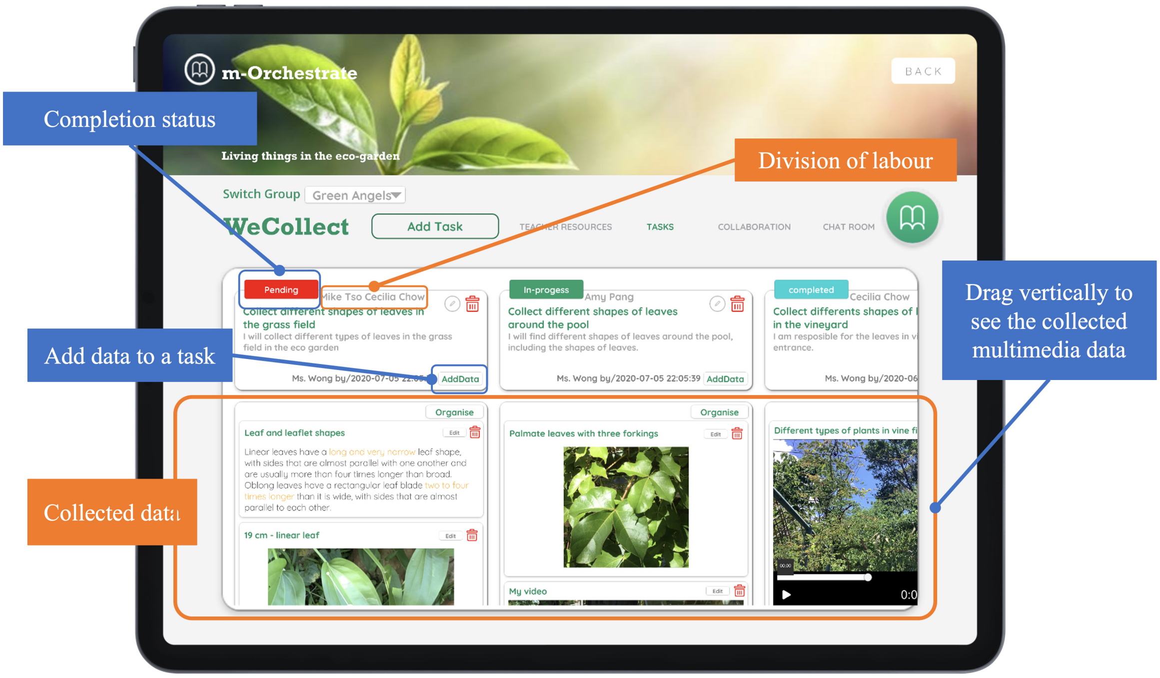


4.1.4.4 WeCollect Phase. During the WeCollect phase, students use the m-Orchestrate app to plan and conduct their own scientific inquiry projects. The app allows them to define their research questions, hypotheses, variables, and methods, as well as assign roles and tasks to each group member. Students can also collect data in various formats, such as text, pictures, videos, or spreadsheets, using the app's built-in tools. The app helps students organize their data and share it with their peers and teachers. The features in the WeCollect phase are intended to ensure that all group members are actively involved in the research process and that their responsibilities are distributed fairly.

Some screenshots are captured from the WeCollect phase of the m-Orchestrate app's interface. The first screenshot (see Figure 14) includes students' interface in the WeCollect phase to facilitate data collection and sharing among group members. Students can add, view, and modify inquiry tasks and select the type of data to collect. This page displays the log and name of the app (m-Orchestrate), the current phase (WeCollect), and the name of the group. Students can collect data directly under a specific inquiry task. The data type button with an icon shows what format of data it is (photo, audio, spreadsheet, or text). The content card displays a preview of the data. Students can tap any data item to view it in a pop-up modal window or delete it by clicking on the recycling bin.

Figure 14

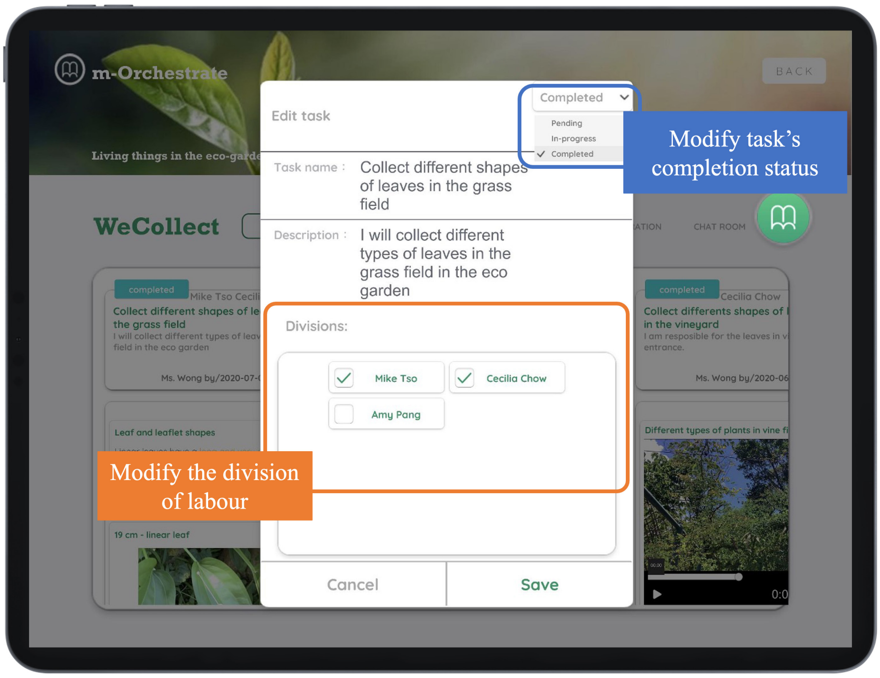
Data Collection in the WeCollect Phase



The second screenshot (see Figure 15) conveys how students can divide their work among themselves by assigning roles and tasks. The interface allows students to modify tasks, task completion status, and work division by tapping on the corresponding elements. A checkbox indicates whether the group member is responsible for the task, and a color-coded circle delineates the division of work. For example, a task assigned to Mike and Cecilia is marked "completed."

Figure 15

Work Division in the WeCollect Phase

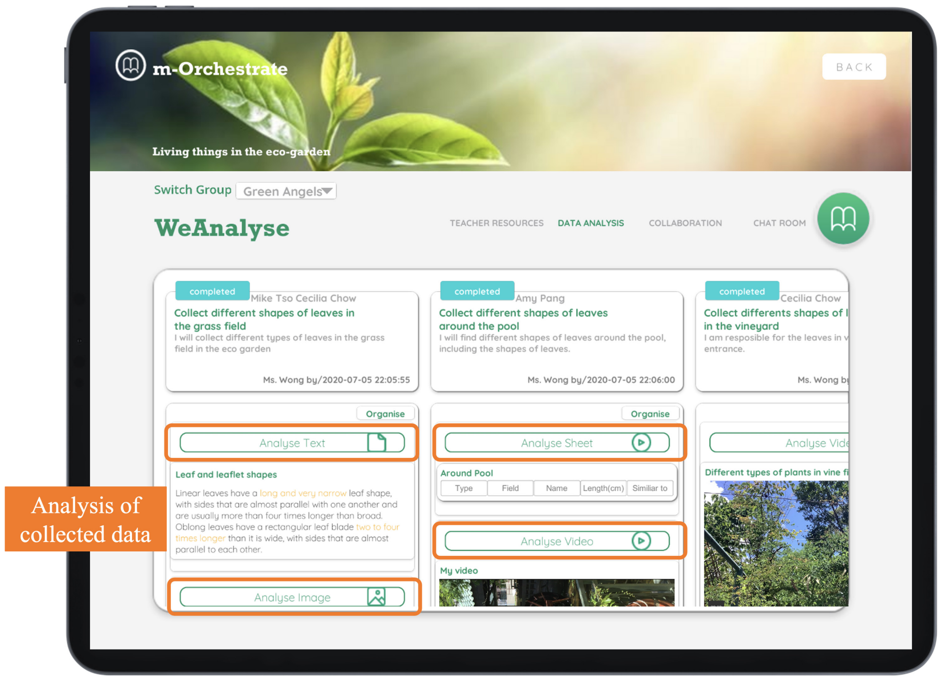


4.1.4.5 WeAnalyse Phase. The m-Orchestrate app allows groups to analyze their collected data in this phase. Whether the data are in text, picture, video, or spreadsheet format, the app can visualize and analyze the data in a variety of ways. The WeAnalyse phase allows group members to gain more insight into the data they have gathered and draw informed conclusions based on their findings. The m-Orchestrate app is also a powerful tool for data analysis. In the WeAnalyse phase, the app enables groups to explore their data in depth. The app supports various types of data, such as text, image, video, and spreadsheet, and allows users to directly pick any collected data in the WeCollect phase (see Figure 16).

As for data visualization strategies, the app provides a range of visualization and analysis options, such as charts, graphs, and tables. Users can easily switch between views and tools to find the best way to present and interpret data. Users can access the feature by tapping the "data analysis" button on the navigation bar. The screen shows a list of all the sources from which the group has collected or imported data. Users can select one or more data sources to view in the main display area. The display area can be zoomed in or out, panned, rotated, or tilted to adjust the perspective. Users can also tap on any data point to see more details about it in a pop-up modal window.

Figure 16

Data Analysis in the WeAnalyse Phase

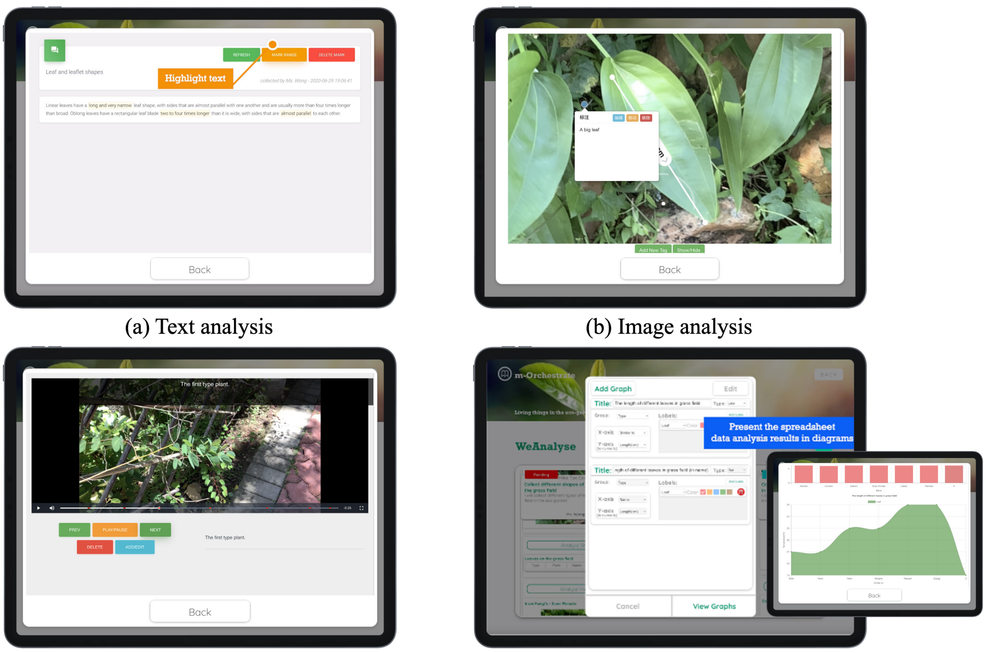


The app also offers a variety of analysis tools that users can apply to their data (see Figure 17).

Users can access the analysis tools by tapping the Analysis icon on the top right corner of the screen. The app will display a menu of available tools, such as pie charts, bar charts, line charts, and scatter plots. Users can select one or more tools to apply to their data. Subsequently, the app generates the corresponding visualization or analysis results in the display area. Users can customize the appearance and settings of each tool by tapping the Settings icon on the top left corner of the screen. Users can also compare tools by swiping left or right on the display area.

Figure 17

Analysis Tools in the WeAnalyse Phase



(a) Text analysis (b) Image analysis

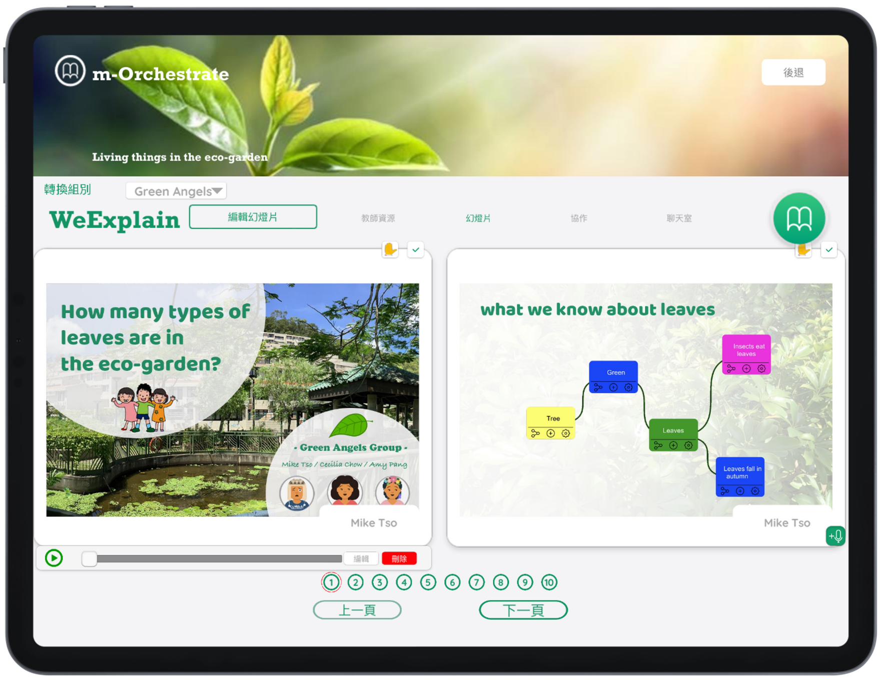
(c) Video analysis (d) Spreadsheet analysis

4.1.4.6 WeExplain Phase. WeExplain is a phase in the m-Orchestrate app that enables groups to present and share their inquiry processes with others. The app supports various types of data sources, such as text documents, images, videos, and spreadsheets, and allows users to visualize and analyze them using different tools and methods. The app also provides a slideshow feature that lets users create and edit slides with their data and annotations. This phase helps group members to deepen their understanding of the data they have collected and to communicate their results and findings effectively (see Figure 18).

The app allows users to customize their slides. Users can also add text boxes, shapes, charts, graphs, and other elements to their slides to create their presentation. Users can also insert audio or video recordings to narrate their slides or to provide additional information. The editor also supports collaborative editing and feedback in the WeExplain phase. Users can invite other group members or external reviewers to view or edit their slides. Users can also comment on each other's slides or use the chat feature to discuss their ideas and suggestions. The app also allows users to export their slides as PDF files or share them online via email or social media platforms.

Figure 18

A Slideshow in the WeExplain Phase

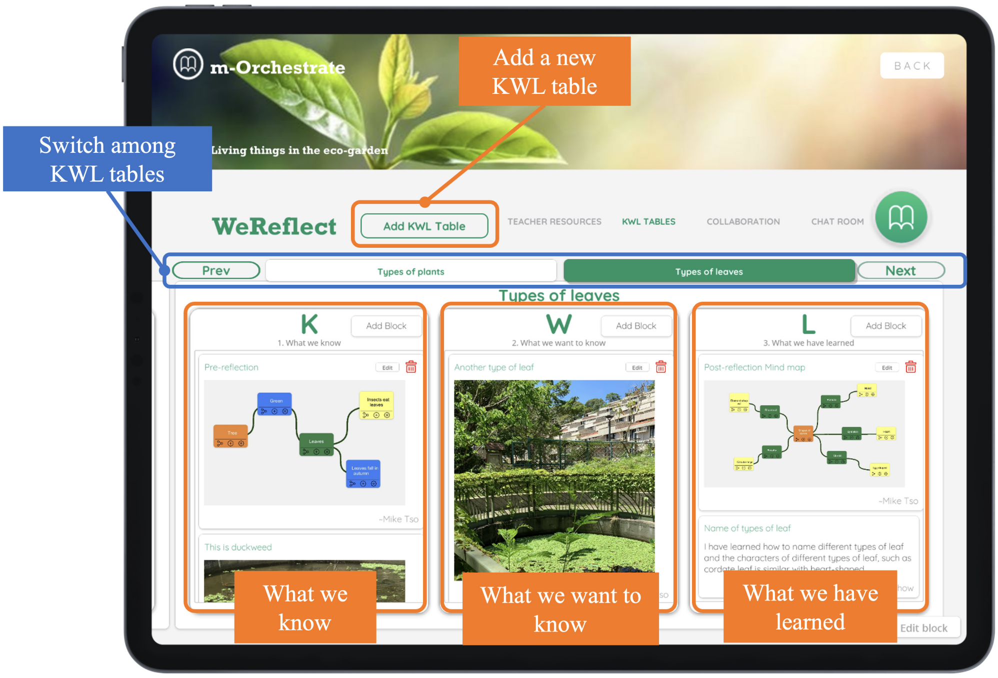


4.1.4.7 WeReflect Phase. WeReflect helps users to reflect on their learning process, using multimedia resources to review prior knowledge, raise questions that they want to learn more about, and discuss challenges they faced during the inquiry process.

One of the core features of WeReflect is that it allows users to create a Know-Want-Learned (KWL) table to track their progress and understanding. A KWL table is a graphic organizer that helps learners organize information before, during, and after a learning activity. The KWL table has three columns: K stands for what the learners "know" about the topic, W represents what they "want" to learn, and L signifies what they "learned" after completing the activity. The m-Orchestrate app enables users to create a KWL table using their mobile devices. Users can enter text, images, audio, or video in each table column. They can also share their tables with other users or with their instructors. Figure 19 demonstrates an example of a KWL table created by a user using the m-Orchestrate app.

Figure 19

A KWL Table in the WeReflect Phase



Another feature for students' reflection needs is the collaborative mind map (see Figure 20), which allows students to collaboratively create a mind map. The provided mind map is a visual tool that can help students organize ideas, connect prior knowledge, and generate new insights during collaborative inquiry-based science learning. They can use different shapes, colors, icons, and images to represent their concepts and relationships. They can also add notes, links, and attachments to their mind map nodes for elaboration. The app allows students to share their mind maps with other groups, comment on each other's work, and revise their own mind maps based on feedback.

Figure 20

Collaborative Mind Map in the WeReflect Phase

4.2 Phase II—Development of a Theory-Led Learning Analytics Tool

The purpose of this phase is to develop a theory-led Learning Analytics (LA) tool embedded in the m-Orchestrate app for teacher orchestration of Collaborative Science Inquiry (CSI) in an Mobile Learning Environment (MLE). Phase II consisted of two main activities: (1) designing and developing the theory-led LA tool and (2) debugging and testing it (see Table 5). The first activity, designing and developing the theory-led LA tool, started in November 2020 and ended in January 2021. This activity lasted three months. The second activity in the table, debugging and testing the LA tool and preparing for Phase III, started and ended in February 2021. This activity lasted one month.

Table 5

Research Activities in Phase II

Activity in Phase II	Time and period		
	Start	End	Duration
Design and develop the theory-led learning analytics tool	Jun. 2020	Jan. 2020	6 months
Debug and test the learning analytics tool	Jan. 2020	Mar. 2020	2 months
Preparation for Phase III			

Phase II of this study focused on the design and development of the proposed theory-led LA tool, debugging, and preparation to implement the tool in Phase III.

4.2.1 The Theory-Led LA Tool

Phase II of the study aimed to develop the proposed LA and properly prepare its orchestration functions. The LA tool was developed to work with the m-Orchestrate app.

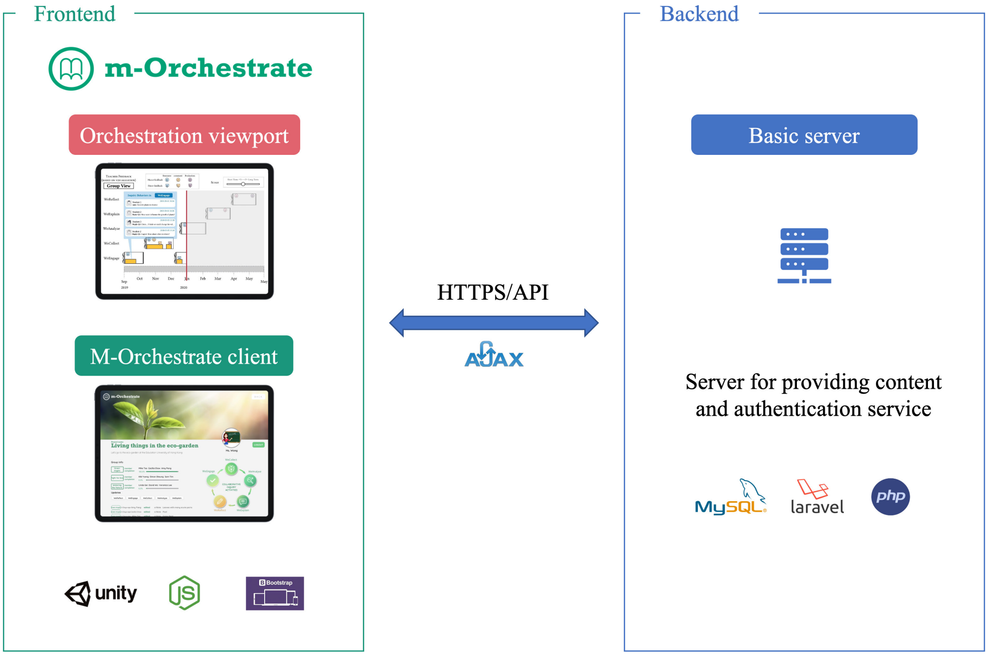
4.2.1.1 Theoretical Underpinnings. The theoretical underpinnings of the LA tool are based on social constructivism theories (Vygotsky, 1978) that support collaborative inquiry-based learning in science. The tool aims to help teachers orchestrate students' inquiry activities by providing them with visualizations of the inquiry process and outcomes, and by enabling them to intervene in a timely and adaptive manner according to the orchestration principles of awareness, continuity, and flexibility.

4.2.1.2 Technical Hierarchy. The hierarchy of the LA tool includes three primary layers for collecting, analyzing, and visualizing data. The first layer links the LA tool with the database of the m-Orchestrate app to retrieve logged data from its MySQL database. The second layer mainly uses Hypertext Preprocessor (PHP) and Python algorithms to process the logged data and sort relationships and occasions worth mentioning for teacher orchestration. The third layer visualizes information in a theory-led and interactive viewport, namely, an orchestration viewport. The layout of the viewport is aligned with the CSI learning model underpinned by social constructivist theories.

The LA tool design framework in Cycle 1 consists of front-end and back-end components to execute teachers' needs for orchestrating CSI (see Figure 21). The framework also illustrates the interactions between these components and the users (i.e., teachers and students) in a cyclical process. The framework is based on the principles of DBR and LA. Raw data include learners' logged interactions and behavior. The data can be captured and stored from the m-Orchestrate app via the HyperText Transfer Protocol (HTTP), Application Programming Interface (API), and Asynchronous Javascript And XML (AJAX) protocols. The basic server implemented in Cycle 1 can visualize students' learning activities on the orchestration viewport. The visualized information can be used to provide feedback to inform teaching practices, improve learning outcomes, and identify problems and suitable opportunities for orchestration. The data flow starts with the log data of the m-Orchestrate app. The LA tool collects and analyzes data from learning activities and provides feedback to teachers. Teachers can use interactive features to improve their learning outcomes and experiences. This process can be repeated to achieve continuous inquiry processes among teachers and students.

Figure 21

System Framework of the Designed LA Tool



4.2.1.3 The m-Orchestrate App embedded with the LA Tool. The m-Orchestrate learning app aims at helping teachers orchestrating CSI (Song et al., 2019), which supports real-time interactions among teachers and students based on a collaborative inquiry model. The design of the m-Orchestrate app aligns with the CSI model with five inquiry phases: WeEngage, WeCollect, WeAnalyse, WeExplain, and WeReflect. The LA tool was developed on the m-Orchestrate app to analyze log data collected from teacher orchestration of students' CSI activities in an MLE.

4.2.1.4 Log Data on the m-Orchestrate App. Table 6 illustrates students' inquiry log data on the m-Orchestrate app, a mobile learning system that supports teacher orchestration and student CSI in an MLE. The collaborative inquiry-based learning model, consisting of five phases: WeEngage, WeCollect, WeAnalyse, WeExplain, and WeReflect is embedded on the m-Orchestrate app. The table presents the inquiry phase, the features of the app, and the logged behaviors of students' inquiry for each phase. For example, in the WeEngage phase, students can use the Inquiry Question feature to ask and comment on inquiry questions. In the WeCollect phase, students can use the task-planning feature to plan, report, and divide inquiry tasks and the data-input feature to collect multimedia data. The table demonstrates how the app facilitates students' collaborative inquiry learning through various features and functions.

Table 6

Students' Inquiry Log Data in the M-Orchestrate App

Inquiry phase	Feature	Logged behaviors of students' inquiry
All phases	Note	Publish a multimedia note
	Mind map	Make a collaborative mind map
WeEngage	Inquiry question	Raise an inquiry question
		Comment on an inquiry question
WeCollect	Task planning	Plan an inquiry task
		Report the status of an inquiry task
		Delegate tasks
	Data input	Collect multimedia data
WeAnalyse	Data analysis	Analyze multimedia data
WeExplain	Slideshow	Upload PPT slides
WeReflect	KWL table	Create a KWL table
		Compose reflections in multimedia

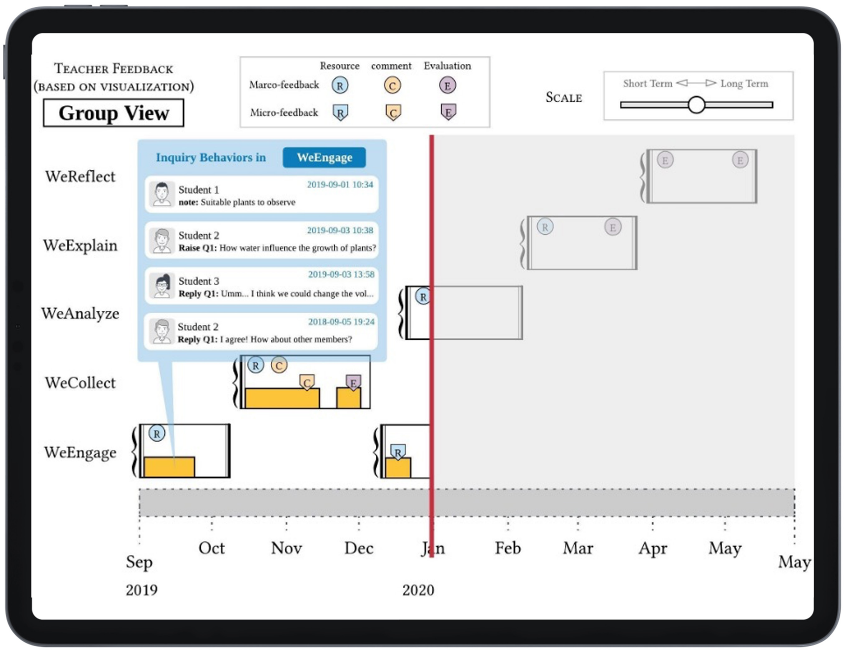
4.2.2 Orchestration Viewport of the LA Tool

LA tool information is mainly presented on a portal, namely, an orchestration viewport. The first design version of the orchestration viewport was published in a workshop paper at the 10th Conference on Learning Analytics and Knowledge (LAK20), respectively (Cao & Song, 2020). The orchestration viewport (see Figure 22) was underpinned by the CSI model and orchestration principles to address the previously mentioned teachers' needs. All inquiry behaviors in the five phases are presented in different tracks, where overlapping and non-linear processes are visualized. Dragging the sliding bar to the top right can zoom in or out of the timeline. In each track, the upper part presents both the circle icon as macro-feedback (in the classroom context) and the tag icon as micro-feedback (for a specific group). The feedback is in three types – resource (i.e., a related article to explain focused issues), comment(i.e., some instructions to overcome barriers during collaborative inquiry), and evaluation(i.e., a related quiz to help students review their knowledge grasping and understanding). In its lower part, horizontal bars nest a series of inquiry behaviors simultaneously. The bars can be clicked on to view specific activities in a pop-up bubble. Next, teachers can interact with the dashboard as follows:

- Dragging and arranging feedback among the five phases with continuity,
- Checking inquiry behaviors to raise awareness of students' activity state,
- Deploying three types of feedback both in advance and on the fly with flexibility,
- Releasing feedback with the integration of micro- and macro-feedback scenarios.

Figure 22

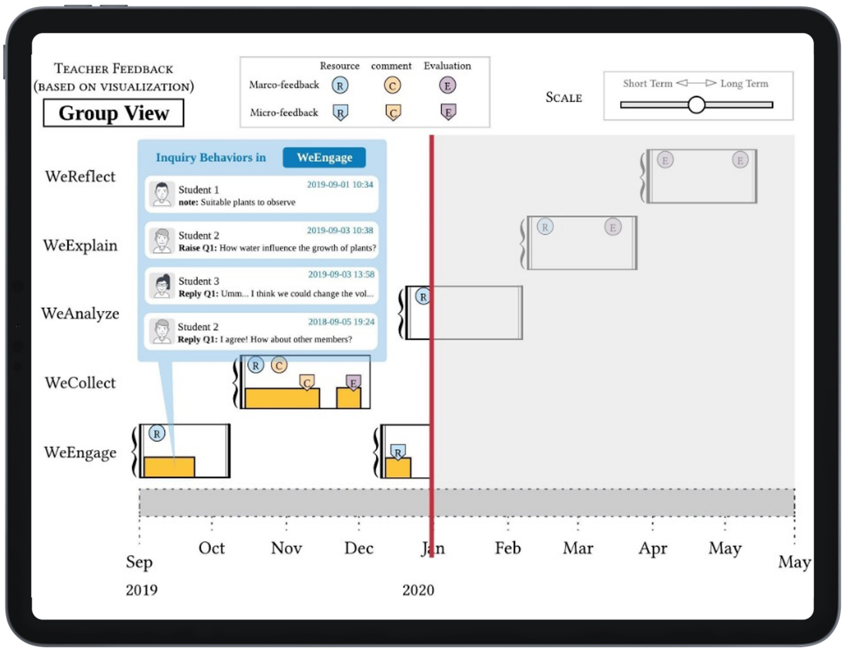
Orchestration Viewport Interface Design of of the Developed Learning Analytics Tool



4.2.2.1 The Learning Analytics Tool's Awareness Feature. The awareness feature helps teachers to monitor students' activities and progress in real time (see Figure 23). This feature consists of two main components. The progress indicators show the percentage of completion for each phase of the inquiry cycle for each group. The indicators are color coded to indicate different levels of progress: green for "completed," yellow for "in progress," and red for "not started." The notifications alert teachers to pay attention to certain events or situations that may require their intervention or feedback. For example, a notification may inform the teacher that a group has changed its inquiry question or that a group has not collected any data for a long time.

Figure 23

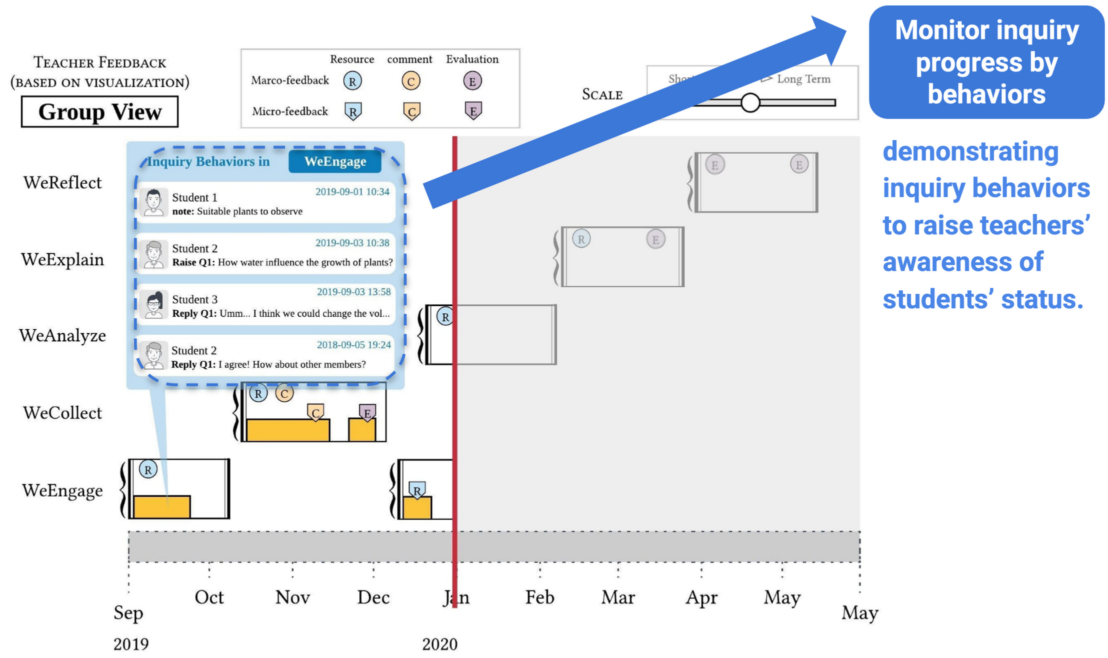
Supporting the Awareness Purposes of the Developed Learning Analytics Tool



4.2.2.2 The Learning Analytics Tool's Continuity Feature. The continuity feature helps teachers to facilitate students' seamless transition between formal and informal learning settings (see Figure 24). The tool allows teachers to monitor the inquiry progress of students according to their behaviors, such as collecting and analyzing data, explaining findings, and reflecting on learning processes. The tool also provides features that demonstrate the inquiry behaviors of students to inspire teachers to conduct relevant interventions according to their updated status and needs. For instance, the tool displays irrelevant data collected by a group of students. Once noticed, teachers can remind them of the problem and provide suggestions.

Figure 24

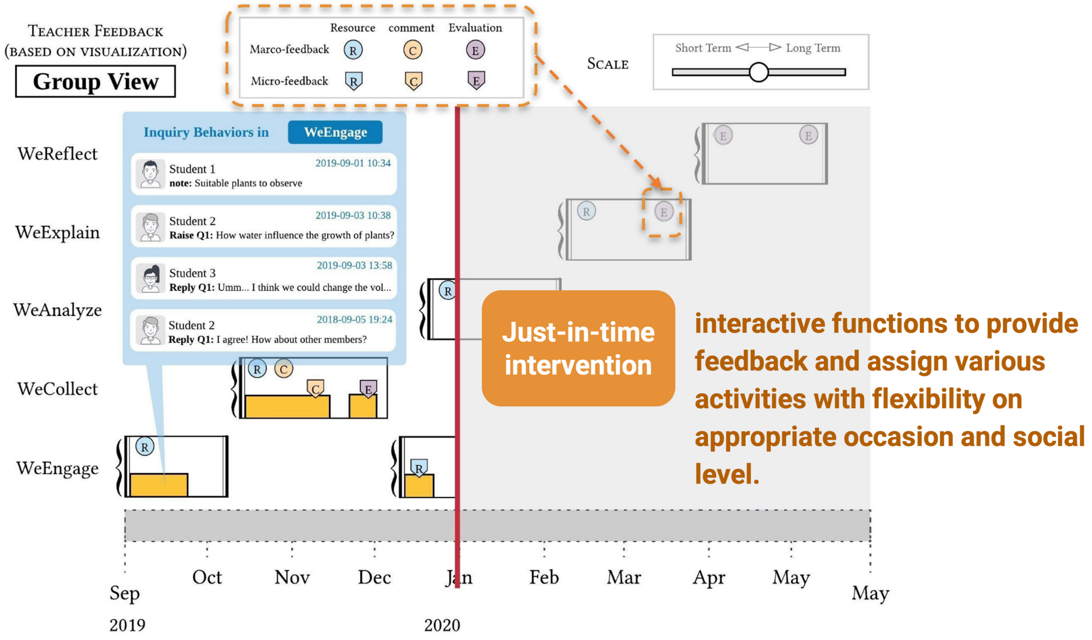
Supporting the Continuity Purposes of the Developed Learning Analytics Tool



4.2.2.3 The Learning Analytics Tool's Flexibility Feature. The flexibility feature in the orchestration viewport is also available in all phases of the inquiry cycle (see Figure 25). The flexibility feature helps teachers adapt and customize the inquiry activities according to students' needs and interests among the assorted groups. The phase selector allows teachers to provide resources between the phases of the inquiry cycle at any time. For example, a teacher may suggest that students skip the WeEngage phase if they are already familiar with the topic. Alternatively, a teacher might recommend that students revisit the WeCollect phase if they need to collect more data. The resource library allows teachers to access and share resources related to the inquiry topic. For example, a teacher may provide articles or websites for students to read before or after inquiry activities.

Figure 25

Supporting the Flexibility Purposes of the Developed Learning Analytics Tool



4.2.3 Usability Test

In Phase II, a usability test (Reimann, 2016) was conducted to evaluate the effectiveness and user friendliness of the affordances of the LA tool in terms of awareness, continuity, and flexibility in supporting teachers' CSI orchestration. Two pre-service science teachers (a male teacher, Sam; a female teacher, Amy) were invited as student helpers to assist with the trial, debug the LA tool, and report technical issues. The outcomes of each trial use and usability test were used to make recommendations for refining the design and developing the LA tool. In this usability test, the internal test and continuous refinement aimed to make the core functions of the LA tool work normally to meet the research needs.

4.2.3.1 Data Collection. The test involved two pre-service teachers, Sam and Amy, who interacted with the LA tool and provided feedback on its usability, functionality, and effectiveness. The interviews with the pre-service teachers were audio-recorded and transcribed, which served as the primary data collection method. The transcripts of the interviews were used for further analysis.

4.2.3.2 Data Analysis. Inductive thematic analysis (Braun & Clarke, 2006; Guest et al., 2012) was employed to analyze data collected from teacher interviews focusing on the key orchestration principles of awareness, continuity, and flexibility in using the LA tool for teacher orchestration of CSI activities. The transcribed data were coded and categorized into themes and sub-themes to identify patterns and insights regarding the usability of the LA tool.

4.2.3.3 Results. The analysis of the interviews yielded the following themes and sub-themes, as displayed in Table 7 with sample scripts.

Sam acknowledged the advantages of using the m-Orchestrate app and the LA tool in orchestrating CSI activities. He emphasized the features to analyze data on student performance and engagement to adjust his teaching approach and provide targeted support and clarification on complex scientific concepts. Amy highlighted the valuable insights provided by the LA tool in tracking students' engagement and progress. She found it beneficial to track the time students spent on each activity and identify completed activities. The tool helped identify students struggling with specific concepts through their performance on quizzes and assessments, enabling the provision of more support and guidance. Amy emphasized the flexibility offered by the LA tool in adapting her teaching methods. He used the tool to identify students struggling with specific scientific concepts and provided additional resources, such as videos, readings, or hands-on experiments, to enhance understanding. The tool let her cater to students' diverse learning needs by adapting her teaching strategies accordingly.

The results of the usability test conducted during Phase II revealed positive perceptions and practical benefits of the LA tool from pre-service teachers. The tool was perceived as advantageous for orchestrating CSI in terms of growing "awareness" of students' inquiry learning process because it could make student performance and engagement data "visible" by visualization. It also supported "flexibility" in orchestrating CSI by enabling teachers to adjust their teaching approach and provide targeted support for complex scientific concepts.

The LA tool facilitated "continuity" in teaching by providing valuable insights into students' engagement and inquiry progress, such as tracking their time spent on activities and identifying areas of difficulties and misconceptions through quizzes and assessments. This information helped teachers provide additional resources and adapt their teaching methods, ensuring personalized support and flexibility in addressing students' diverse learning needs. These findings highlighted the effectiveness of the LA tool in supporting teacher orchestration and informed decision making in science education. The feedback received from the pre-service teachers also informed the refinement and further development of the tool for Phase III implementation.

After the usability test, three iterative cycles were conducted to implement and refine the LA tool in the m-Orchestrate app. Meanwhile, the researcher submitted the ethics review to the Human Research Ethics Committee (HREC) and sought approval before recruiting human participants. Due to the COVID-19 pandemic, students and teachers could not attend face-to-face classes at school, so they used Zoom to conduct online classes along with the m-Orchestrate app to facilitate remote inquiry-based learning.

Table 7

Thematic Analysis of Pre-Service Teacher Interviews in Phase II

Theme	Sub-theme	Script
Awareness	Perceptions of the LA tool	"As a teacher, I believe that using the m-Orchestrate app and the LA tool has several advantages in teaching science. By analyzing data on student performance and engagement, I can adjust my teaching approach to provide more targeted support and clarification on complex scientific concepts." (Sam)
Continuity	Benefits of resources and feedback based on learning trajectories	"The tool provided valuable insights into students' engagement and progress. I was able to track how much time students spent on each activity and which activities they completed. It also helped me identify students who were struggling with specific concepts through their performance on quizzes and assessments." (Amy)

Continued on the next page

Table 7

Thematic analysis of pre-service teacher interviews in Phase II (cont.).

Theme	Sub-theme	Script
Flexibility	Adaptation of teaching methods	"The LA tool provided valuable insights into students' engagement and progress in science. If the tool indicated that a particular student was struggling with a certain scientific concept, I would provide additional resources, such as videos, readings, or hands-on experiments, to help them better understand the material." (Amy)

The end of the table

4.3 Phase III—Iterative Cycles of Implementation and Refinement of the Learning Analytics Tool for Teacher Orchestration

After refining the m-Orchestrate app and developing a theory-led Learning Analytics (LA) tool, the LA tool was implemented in Collaborative Science Inquiry (CSI) and orchestration practices in a Mobile Learning Environment (MLE) in Hong Kong primary schools. The entire implementation phase aimed to adopt and refine the LA tool to improve orchestration practice which referred to the skill of coordinating and managing multiple IT systems and applications efficiently and effectively. It comprised three iterative cycles and lasted for 18 months in total. Each cycle lasted for six months (see Table 8). Regarding the design, implementation, reflection, and refinements of the LA tool, the following Research Questions (RQs) of this study were addressed in three iterative cycles in this phase.

RQ1: What are the affordances of the LA tool regarding theory-led and interactive design for the teacher orchestration of CSI?
RQ2: What is the impact of the theory-led LA tool on teachers' orchestration of CSI?
RQ3: What is the impact of teacher orchestration supported by the theory-led LA tool on students' CSI performance?

Table 8 shows the DBR activities in Phase III of a project that aimed to improve orchestration practice.

The first cycle explored how the affordance of the LA tool could support teacher just-in-time orchestration with the interactive features in CSI in an MLE, and adaptation to changing needs and situations. The second cycle investigated how the affordance of the LA tool could support orchestration practices with Business Process Analytics in R (bupaR) to provide insights into students' CSI learning processes. The third cycle examined how the affordance of the LA tool could support orchestration practices with Python implementation of the Python implementation of the Bayesian Knowledge Tracing (pyBKT) to identify students' inquiry patterns in each inquiry phase of CSI. The three iterative cycles started in September 2020 and ended in February 2022.

Table 8

Research Activities in Phase III

Activity in Phase III	N. of Participants		Time and Period		
	Teacher	Student	Start	End	Duration
Cycle 1: Implementation of the LA tool with interactive features for just-in-time orchestration	2	50	Mar. 2021	May 2021	2 months
Cycle 2: Refinement and implementation of the LA tool with bupaR for orchestration practice	4	100	May 2021	Nov. 2021	6 months
Cycle 3: Implementation of the LA tool with pyBKT for orchestration practice	4	100	Nov. 2021	May 2022	6 months

The study involved using a mobile app called m-Orchestrate, which supported students' CSI in five phases: WeEngage, WeExplore, WeAnalyse, WeExplain, and WeReflect. The data collection methods included log data from the app, and the LA tool, teacher interviews, and students' domain knowledge of pre- and post-quizzes. Table 9 shows the data sources used to address the RQs.

Table 9

Data Sources Used to Address the Research Questions in Phase III

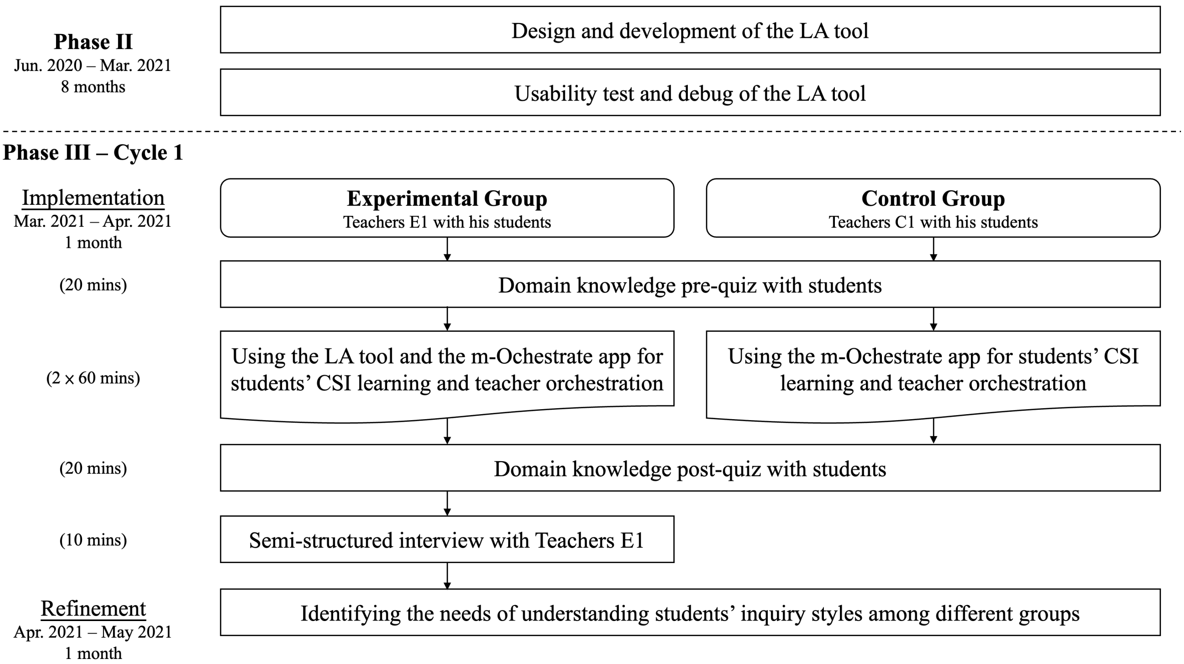
#	Data Source	Research Question (RQ)		
		RQ1	RQ2	RQ3
(1)	Log data in the m-Orchestrate app	✓		
(2)	Teacher interviews	✓	✓	
(3)	Students' knowledge in pre- and post-quizzes			✓

4.3.1 Cycle 1: Implementation of the LA Tool with Interactive Features for Just-in-Time Orchestration

Cycle 1 focused on the implementation of the LA tool developed in Phase II in teacher orchestration of CSI in an MLE. Due to the COVID-19 pandemic, students and teachers could not attend face-to-face classes at school, so they used Zoom to conduct online classes along with the m-Orchestrate app to facilitate remote inquiry-based learning. This research activities include the implementation of the LA tool to investigate the use and impact of the LA tool and the proposing refinement of the LA tool according to the actual orchestration needs identified from the implementation (see Figure 26).

Figure 26

Research Activities in Cycle 1 of Phase III



4.3.1.1 Implementation. The researcher and Teacher E1 co-designed a teaching plan that complied with the features of the m-Orchestrate app and the LA tool. The course topic was "The Eight Planets in the Solar System." The teacher introduced the topic of the Solar System and provided introductory materials on the Eight Planets in the Solar System before students utilized the application to access interactive multimedia resources, such as videos and animations, to deepen their understanding of each planet's unique features. Collaborative activities were assigned via the m-Orchestrate app, requiring students to work together to accomplish tasks such as designing a model of the solar system or planning a mission to explore a planet.

Both activities and materials (including domain tests) were based on the General Studies curriculum of the school, which aimed to assess the student's knowledge and skills in various subjects. The process of co-designing the test with the teachers involved online meetings, training sessions, and iterative feedback. The teachers wrote a plan for the test, which was reviewed and revised by us until it met the quality standards. This way, we ensured that the test was aligned with the learning objectives and outcomes of the curriculum.

The process of implementation in Cycle 1 is presented in Figure 26. Before starting the courses, all students of Teachers E1 and C1 attended a domain knowledge pre-quiz about the eight planets in the Solar system, including nine items (i.e. "The largest planet in the Solar system?"). The courses were conducted with two 60-minute sessions on Zoom with the m-Orchestrate app. Both Teachers E1 and C1 mainly delivered teaching materials and conducted in-class activities on the m-Orchestrate app. Only Teacher E1 also used the LA tool to follow up and intervene in students' CSI process among different groups. Besides in-class activities, students also had some tasks as homework on the m-Orchestrate app between the two sessions. After finishing the second session, the students from Teachers E1 and C1's classes attended a domain knowledge post-quiz, which was the same as the pre-quiz. The semi-structured interview was conducted in English to investigate the teacher (Teacher E1) from the experimental group on the interactive features of the LA tool for orchestration principles in terms of awareness, continuity, and flexibility and lasted 10 minutes.

4.3.1.1.1 Participants. In this cycle, two teachers (Teacher E1—a male; and Teacher C1—a male) and two classes of their students participated. Teacher E1 and his students used the newly developed LA tool with the m-Orchestrate app as the experimental group. Teacher C1 and his students also used the m-Orchestrate app without using the LA tool. Both classes were in Grade 4 with 25 students respectively, and their target class topic was the Eight Planets in the Solar System. All students have their fixed inquiry groups according to existing arrangements by their teachers.

4.3.1.1.2 Data Collection. In Cycle 1, collected data includes (1) teachers' operation records on the LA tool on the m-Orchestrate app, (2)semi-structured teacher interviews, and (3) students' scores on domain knowledge pre- and post-quizzes.

Operation Records on the LA Tool. The log data of Teacher E1's operation on the LA tool were analyzed to identify when and how teachers orchestrate CSI learning activities using the LA tool.

Teacher Interview. A 10-minute semi-structured teacher interview was conducted after this cycle to determine teachers' perceptions of and experience with using the LA tool to orchestrate CSI. The interview was audiotaped and conducted in English (see cleaned transcripts in Appendix B).

Student Domain Knowledge Pre- and Post-Quizzes. Students' scores on pre-quizzes and post-quizzes were conducted to examine their understanding of the Solar system and its eight planets (see Appendix C). The researcher designed the test and negotiated with the participating teachers to match their learning content and objectives. There were 24 (from the experiment group) and 19 (from the control group) valid responses of student domain knowledge pre- and post-quiz collected in this cycle.

4.3.1.1.3 Data Analysis. Cycle 1 focused on the interactive features of the LA tool for orchestration principles in terms of awareness, continuity, and flexibility, and their impact on teacher orchestration and student learning in an MLE. The data analysis methods were: (1) bupaR analysis, (2) inductive thematic analysis, and (3) independent and paired-sample t-tests. The following subsections describe each method briefly.

bupaR Analysis of Operation Records on the LA Tool. bupaR analysis is a process mining technique that can extract and analyze information from event logs. BupaR analysis was used to generate process maps and a process matrix that showed how teachers interacted with the LA tool's features in this cycle and how their interactions changed over time. The analysis also compared teachers' interactions across cycles, groups, and contexts. The results of the bupaR analysis could help understand teachers' adoption, usage, and perception of the LA tool, as well as their pedagogical strategies and challenges in facilitating students' CSI learning in an MLE.

Inductive Thematic Analysis of Teacher Interview. To analyze transcripts from online semi-structured interviews with teachers using the LA tool, an inductive thematic analysis approach was employed. This method involves a comprehensive analysis of the original contents in an interview. In this process, the transcripts were read carefully and categorized into themes and codes based on data patterns and emerging insights of feedback on the interactive features for just-in-time teacher orchestration needs with the LA tool.

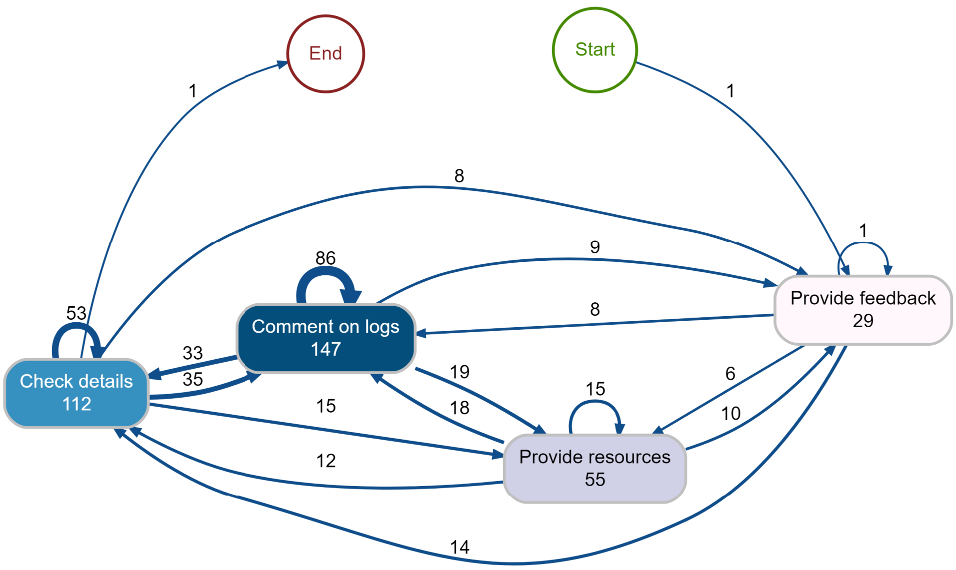
Independent and Paired-Sample T-Tests of Student Domain Knowledge Pre- and Post-Quizzes. To examine the effects of the LA tool on students' learning outcomes, t-tests were conducted on the scores of students' pre- and post-quizzes in each cycle. The quizzes were designed to assess students' understanding of the course content and inquiry skills. SPSS software was used to compare the mean scores of the pre- and post-quizzes for each cycle.

4.3.1.1.4 Results.

Teacher E1's Operation Records on the LA Tool. Although in earlier applications, we could observe the details of student activities, teachers could not make corresponding annotations, feedback, and interventions directly based on students' CSI learning activity records (see Figure 27). Therefore, after we developed our learning analysis tool, we provided four main functions to teachers to offer flexible, convenient, and direct interventions. For example, after checking the details, teachers can directly evaluate students' activity situations. At this stage, teachers' utilization of this tool is presented and analyzed in the following figure.

Figure 27

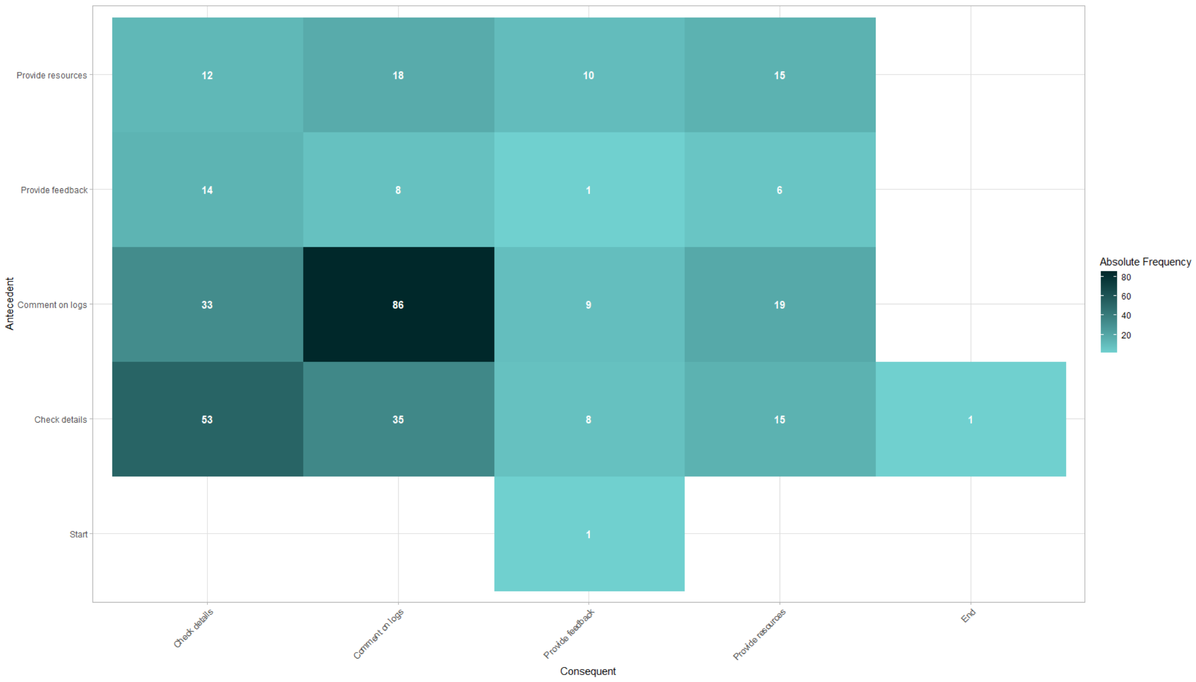
Process Map of Teacher E1's Operation in Cycle 1 by BupaR



In the first cycle, Teacher E1 participated in four main events in Figure 28. One was checking the details, one was commenting on students' notes, and one was providing resources to the teacher and feedback on students' activities, as we can see. Teachers' most frequently used function of this tool was commenting on students' activity records, reaching 147 times, and observing their activity progress, with a frequency of 112 times. Based on their activity situations, Teacher E1 provided teacher resources 55 times. From the matrix chart, we can also see that their activities mainly consisted of checking and commenting on activity records. Consequently, few operations provided feedback.

Figure 28

Process Matrix of Teacher E1's operation in Cycle 1 by BupaR



Teacher Interviews. The interview with Teacher E1 in Cycle 1 discusses the perception and use of an LA tool in the m-Orchestrate app in teaching the Eight Planets in the Solar System. The tool allows the teacher to track student engagement and identify areas where students need additional support. However, there are potential challenges associated with data overload and the limited scope of the tool. The LA tool allows the teacher to provide resources and feedback based on different learning trajectories, but the tool may not capture the full extent of engagement and understanding. The teacher uses the LA tool to monitor students' progress and engagement, to make informed decisions about supporting their learning goals, and to adjust teaching strategies as needed (see Table 10).

However, potential challenges were associated with using the LA tool in the m-Orchestrate app. One of these was the potential for data overload. The tool generated a large amount of data, which could be overwhelming to process and interpret. It was important to have systems in place for analyzing and interpreting data and for focusing on the most important and actionable insights. Another potential challenge was the limited scope of the tool. Although it could track and analyze data within the app, it may not have captured the full scope of students' learning. Therefore, it was important to use the tool with other forms of assessment and evaluation. The cleaned interview transcripts are attached to Appendix B.

Table 10

Thematic Analysis of Teacher Interview in Cycle 1

Theme	Sub-theme	Script
Awareness	Perceptions of the LA tool	"As a teacher, I found that using the m-Orchestrate app to teach a lesson on the Eight Planets in the Solar System had several advantages." (Teacher E1)
		"By analyzing data on student performance and engagement, I was able to adjust my teaching approach to provide more targeted support and clarification on challenging concepts." (Teacher E1)
Continuity	Benefits of resources and feedback based on learning trajectories	"The tool allowed me to track how much time students spent on each activity and which activities they completed." (Teacher E1)
		"I could see which students were struggling with specific concepts based on their performance on quizzes and assessments and provided additional support and guidance as needed." (Teacher E1)

Continued on the next page

Table 10

Thematic Analysis of Teacher Interview in Cycle 1 (cont.).

Theme	Sub-theme	Script
	Limitations of the LA tool	"The tool may not have captured the full extent of student engagement and understanding, as some students may have been more comfortable asking questions or engaging with the material in other ways." (Teacher E1)
		"There were limitations to the data types that could be tracked by the tool, which may have limited its ability to provide a complete picture of students' inquiry status." (Teacher E1)
Flexibility	Use of the LA tool's information for providing resources and feedback	"If the tool indicated that a particular student was struggling with a certain concept, I would provide additional resources, such as videos, readings, or practice problems, to help them better understand the material." (Teacher E1)
		"Then I would adapt my teaching methods to provide more targeted support and clarification." (Teacher E1)

Continued on the next page

Table 10

Thematic Analysis of Teacher Interview in Cycle 1 (cont.).

Theme	Sub-theme	Script
	Ongoing assessment and improvement	"By using it to monitor student progress and engagement, I can make informed decisions about how best to support their learning goals over time." (Teacher E1)
		"Adjust my teaching strategies as necessary to better meet their needs." (Teacher E1)

The end of the table

Student Domain Knowledge Quizzes. An independent t-test showed there was a significant difference between the total scores of pre-domain knowledge quizzes in experimental and control groups in Cycle 1 ($p < 0.05$), indicating there was no significant difference observed in students' prior science knowledge. An independent t-test was further conducted to examine the total scores of post-domain knowledge quizzes. The results showed that there was a significant difference between the total scores of post-domain tests in experimental and control groups in Cycle 1 ($p < 0.05$).

A paired-sample t-test was used to determine whether there was a statistically significant mean difference in pre- and post-domain tests in Cycle 1. Statistical analyses were run using SPSS Version 26. Table 11 reveals no significant disparity between the total scores of the pre-domain test ($M = 69.96, SD = 5.91$) and post-domain test ($M = 71.00, SD = 5.88$) in the class of Teacher C1 as the control group, the difference in 95% CI $[-.2.22, 4.30]$, $t(25) = .658$, $p > .05$, suggesting that learners' knowledge advancement in the control group did not notably improve after using m-Orchestrate in collaborative inquiry during Cycle 1.

Table 11

Paired-Sample T-Test of Student Quiz Results from the Experimental Group in Cycle 1.

	Paired Differences							
				Mean diff. (95% CI)				
	Mean	SD	SEM	Lower	Upper	t	df	Sig. (2-tailed)
post-pre	1.04	7.90	1.58	-2.22	4.30	.658	24	.517

Note. $^{*}: p < 0.05$, $^{**}: p < 0.01$, $^{***}: p < 0.001$

Table 12 depicts no significant difference between the total scores of the pre-domain test ($M = 69.45, SD = 5.91$) and post-domain test ($M = 70.05, SD = 5.84$) in the class of

Teacher E1 as the control group, 95% CI $[-3.40, 4.60]$, $t(20) = .314$, $p > .05$, suggesting that learners' knowledge in the experimental group did not markedly advance after using m-Orchestrate in collaborative inquiry in Cycle 1.

Table 12

Paired-Sample T-Test of Student Quiz Results from the Control Group in Cycle 1.

	Paired Differences							
				Mean diff. (95% CI)				
	Mean	SD	SEM	Lower	Upper	t	df	Sig. (2-tailed)
post-pre	.60	8.54	1.91	-3.40	4.60	.314	19	.757

Note. $^{*}: p < 0.05$, $^{**}: p < 0.01$, $^{***}: p < 0.001$

4.3.1.1.5 To address the research questions (RQs). For RQ1, the theory-led LA tool afforded teachers four main functions: checking details, commenting on notes, providing resources, and giving feedback. The most frequently used functions were commenting and checking, while feedback was less used. The tool enabled teachers to monitor student engagement and performance, identify areas of difficulty, and provide targeted support based on different learning trajectories.

For RQ2, the theory-led LA tool had a positive impact on teacher orchestration in CSI. The tool helped teachers adjust their teaching approach, provide more resources and feedback, and make informed decisions about supporting student learning goals. However, there were also potential challenges associated with data overload and the limited scope of the tool. Teachers needed systems for analyzing and interpreting data and using the tool with other forms of assessment and evaluation.

For RQ3, the theory-led LA tool did not have a significant impact on student learning performance in CSI. There was no significant difference between the pre-and post-domain knowledge quizzes in both experimental and control groups. This suggested that using the tool did not markedly improve students' knowledge advancement in CSI.

4.3.1.2 Refinement. In Cycle 1, the first RQ explored the affordances of theory-led design interactive features of the LA tool for teacher orchestration of student CSI in an MLE. Theory-led design refers to developing novel tools for LA that are based on first principles drawn from theory (Kelly et al., 2015). These interactive features can help teachers to orchestrate online groups in real time by using the LA tool. The results showed that the LA tool had four main interactive features as affordances for teachers: checking details, commenting on notes, providing resources, and giving feedback. The frequency and patterns of teachers' operations on the LA tool were analyzed using BupaR. It shows that Teacher E1 used the LA tool with the developed interactive features.

The second RQ examined the impact of the LA tools on teachers' orchestration. Teacher E1 who used the LA tool in teaching a lesson on the Eight Planets in the Solar System was interviewed, and his operation records on the LA tool were collected. A thematic analysis of the interview transcript identified some themes and sub-themes related to the teacher's perceptions, benefits, limitations, and flexibility of using the LA tool. The results revealed that Teacher E1 made use of the interactive features and found meaningful information provided by the orchestration viewport and the LA tool.

The third RQ investigated the impact of teacher orchestration supported by the theory-led LA tool on students' CSI performance. Student pre- and post-domain knowledge quizzes were conducted for students in experimental and control groups. Independent t-tests and paired-sample t-tests were performed to compare the scores of the quizzes. Students in the experimental group (under Teacher E1's orchestration with the assistance of the LA tool) showed better performance than students in the control group (under Teacher C1's orchestration with the assistance of the LA tool).

The teachers still encountered some difficulties while orchestrating CSI. Collaborative inquiry learning behaviors were distributed in various forms and places. These behaviors were created by multiple stakeholders on specific phases or social levels. Consequently, it is difficult to obtain a bird's-eye view of them at a glance. After the implementation in Cycle 1, teachers still need further support, as follows:

- Recognizing the problems and needs of each group and even the whole class just in time,
- Identifying appropriate strategies to address issues and needs,
- Reviewing the impact of strategy on students' inquiry behavior,
- Making sense of what to facilitate in the next step.

Thus, the refinements identified in this cycle focused on developing the interactive dashboard and then conducting investigations to evaluate the effectiveness of the interactive dashboard in supporting teachers' orchestration of CSI. For visualizing students' CSI learning into more sights, the Business Process Analytics in R (bupaR) was considered to be embedded into the LA tool in Cycle 2. bupaR is a process mining package in R that can be used to analyze students' CSI processes in an MLE.

It has several advantages over other analysis approaches, such as First-Order Markov Models

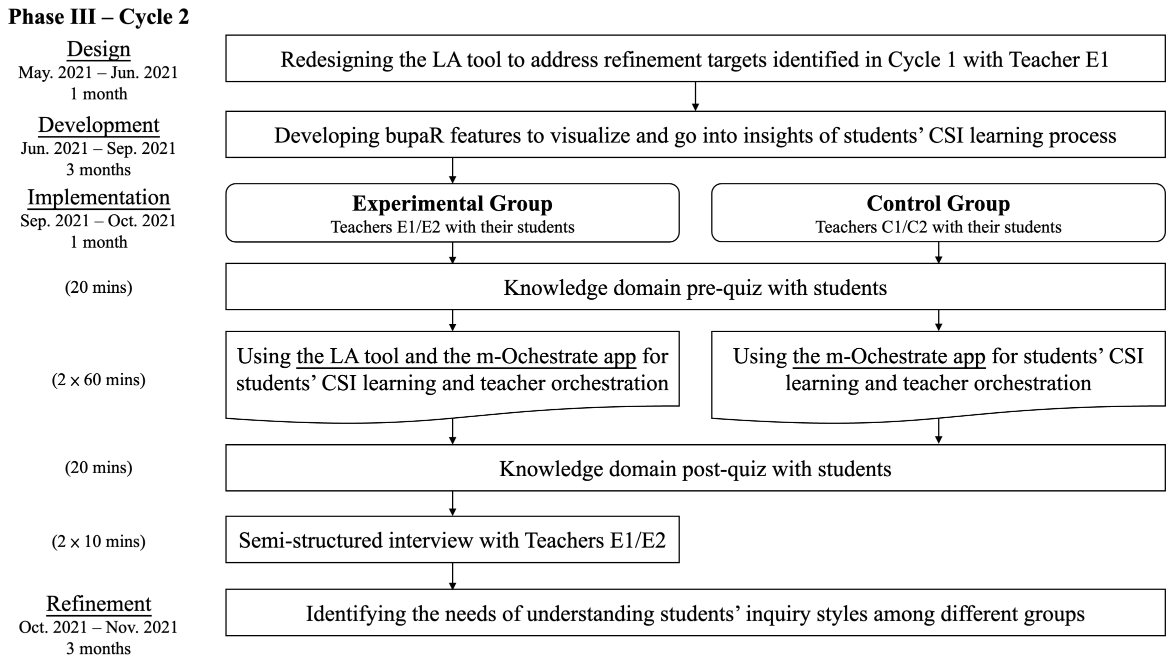
(FOMMs). BupaR can (1) filter, mutate, arrange, group, and join event logs based on various criteria, such as activity, resource, case, or time and (2) create graphical representations of event logs, such as process maps, Gantt charts, dotted charts, and performance spectra. Thus, bupaR can be used to identify the key common and different features in the process of the student CSI behaviors (Song et al., 2022).

4.3.2 Cycle 2: Refinement and Implementation of the LA Tool with bupaR for Orchestration Practice

Cycle 2 of Phase III in the DBR aimed to develop and evaluate an interactive dashboard for teacher orchestration of CSI using LA. This cycle consists of four stages, including (1) redesign, (2) development, (3) implementation, and (4) refinement (see Figure 29). The redesign stage explains how the LA tool was refined with a more advanced and flexible technological solution called bupaR, which could help analyze and go into insights into students' CSI processes from the m-Orchestrate app. The development stage demonstrates how the user interface of the orchestration viewport was enhanced to provide teachers with real-time data on students' inquiry progress, performance, engagement, and collaboration, as well as suggestions and feedback features more clearly. The implementation stage reports how the refined LA tool was used by two teachers and their students from the experimental group in an inquiry-based course, the growth of plant growth, and how data was collected and analyzed using (1) teacher operation records, (2) teacher interviews, and (3) student domain knowledge pre- and post-quizzes. The refinement stage discussed about how the findings from Cycle 2 showed that the orchestration viewport was helpful for teacher awareness, continuity, and flexibility in orchestrating CSI, especially with the insights provided by the newly added bupaR analysis of students' CSI behaviors, but also identified potential can be further addressed and realized in Cycle 3.

Figure 29

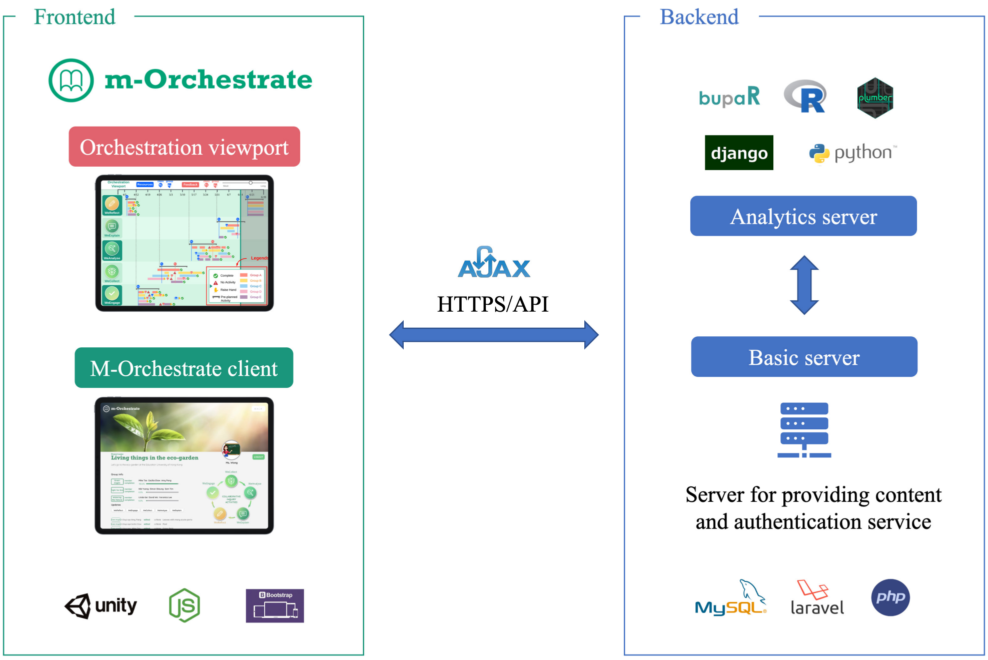
Research Activities in Cycle 2 of Phase III



4.3.2.1 Redesign. The primary refinements in Cycle 2, an LA tool with an orchestration viewport, used a more advanced and flexible technological solution, bupaR, to analyze and visualize students' log data from the m-Orchestrate app (see Figure 30). To solve the slow responses and low performance caused by a traditional Apache web server using PHP scripts, the LA tool adopted Django and Plumber as back-end service solutions in Python and R to realize analysis tasks on the cloud side.

Figure 30

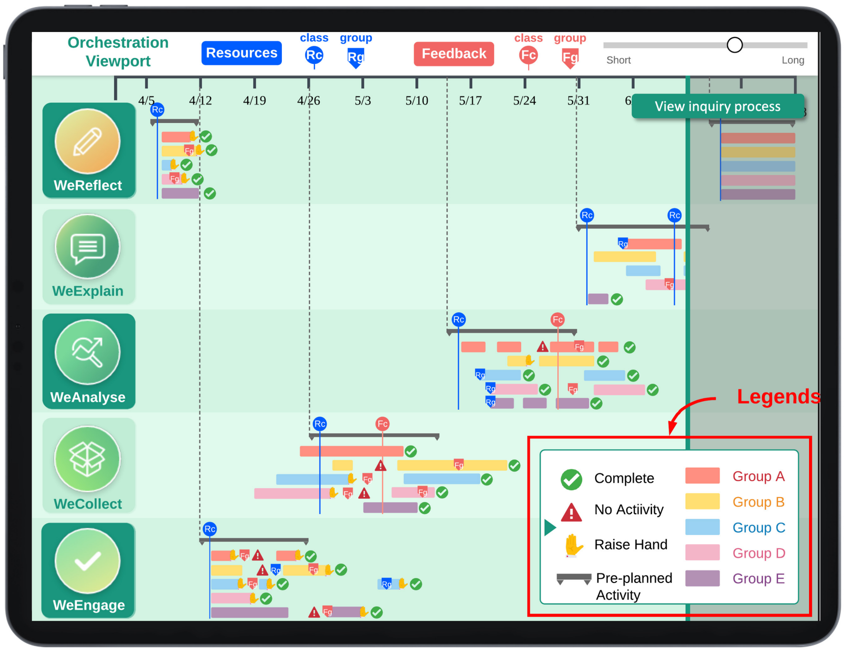
System Framework of the LA Tool Refined in Cycle 2



4.3.2.2 Development. The User Interface (UI) designs of an LA tool before and after refinements are similar in terms of layout features. Both designs show the learner's progress, performance, and goals in different visual elements on the same dashboard, namely, the orchestration viewport. Both designs also use charts, graphs, and colors to visualize students' inquiry activity log data in the m-Orchestrate app so teachers can easily understand it (see Figure 31). However, the first design employs the notation of symphony scores to represent the annotations of different groups of students at different stages of learning, which may confuse teachers. The second design adopted a simpler appearance to demonstrate information more directly. Additionally, the user will find the meanings of each element on the orchestration viewport in the newly added legend panel. A newly added bupaR analysis approach can be reached via the button floating in the top right corner.]

Figure 31

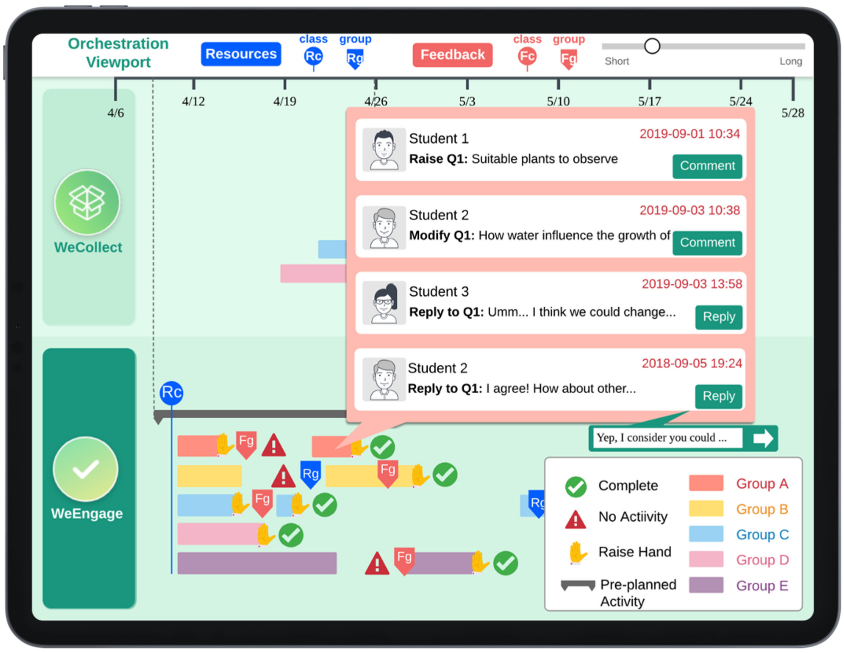
Orchestration Viewport Interface Design of the LA Tool Refined in Cycle 2



The user interface of an orchestration viewport in the LA tool to support teacher awareness is demonstrated in Figure 32. The interface includes charts and graphs to visualize students' progress, performance, and engagement in various learning activities and topics. The tool also provides alerts and notifications highlighting collaborative groups that need attention, assistance, or intervention from the teacher. Furthermore, the tool offers suggestions and recommendations that help teachers plan and adjust their teaching strategies and actions based on data and feedback. The teacher can interact with the tool by selecting disparate options, filters, or views to explore and analyze the data and feedback in more detail.

Figure 32

Supporting the Awareness Purposes of the LA Tool Refined in Cycle 2



The Continuity feature is designed to support teacher continuity after the refinements demonstrated in Figure 33. After simplifying the interface, the flows and paths are more explicit from the new orchestration viewport. The tool uses timelines and histograms to visualize students' learning trajectories and patterns across time, learning activities, and topics. The tool also provides filters and selectors that allow the teacher to customize the views of the data and feedback according to different groups. Furthermore, bupaR offers insights and guidance that help the teacher understand the meaning and implications of the data and feedback. In addition, bupaR suggests actions or interventions to improve students' learning. The teacher can annotate and share the data and feedback with other teachers or stakeholders.

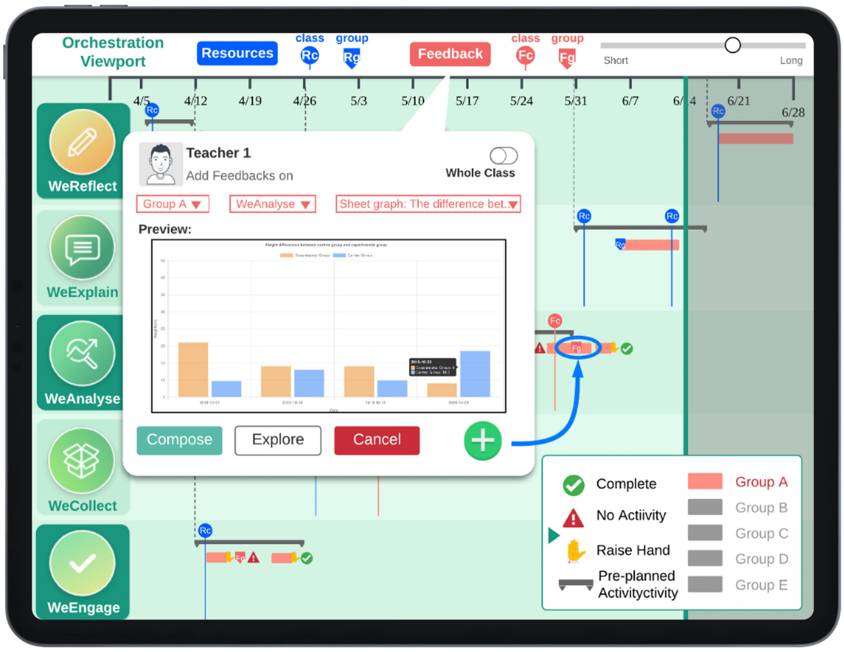
Figure 33

Supporting the Continuity Purposes of the LA Tool Refined in Cycle 2

The features are designed to support teachers' flexibility after the refinements depicted in Figure 34. The tool uses sliders and switches to allow teachers to adjust the parameters and settings of the data and feedback according to their preferences and needs. The tool also provides options and menus that enable the teacher to choose a range of modes, views, or formats of data and feedback according to their goals and purposes. Furthermore, this tool offers feedback features for teachers to address students' specific needs in different learning groups with multiple trajectories. The teacher can modify their interventions as feedback as the need arises.

Figure 34

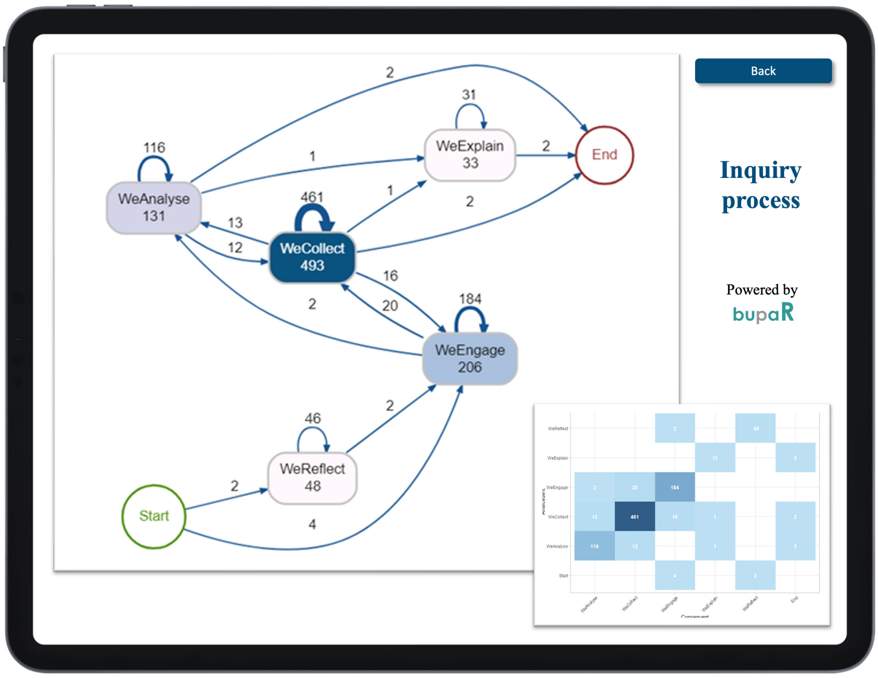
Supporting the Flexibility Purposes of the LA Tool in Refined in Cycle 2



After clicking the "view inquiry process" button, the interface displays the analytic results produced by bupaR (Janssenswillen et al., 2019) (see Figure 35). The Process Map portrays the flow of the students' actions and transitions between tasks, as well as the frequency and duration of each action (see R source codes in Appendix D). A teacher can use this information to understand how the students approach and solve tasks as well as to detect patterns or anomalies in their behavior. For example, a teacher can identify if some students are skipping or repeating tasks, or if they are spending too much or too little time on certain actions. Activities in the matrix will display the intensity of CSI activities among inquiry phases in the m-Orchestrate app.

Figure 35

Viewing the BupaR Outputs of the LA Tool Refined in Cycle 2



4.3.2.3 Implementation. Cycle 2 implemented the refined LA tool for teacher orchestration of CSI in an MLE. The implementation focused on the newly developed user interfaces and bupaR features to go into insights into students' inquiry processes. The implemented course topic was "The Growth of Plants," co-designed by the researcher with four participating teachers. The course lets students learn at their own pace, exploring content and activities based on their curiosity. The teacher introduced the topic and explained the main factors that affect plant growth before the students used the app to find multimedia resources, such as videos and animations, that showed how plants grow in disparate environments. The app also assigned activities that required students to work together to investigate or create projects related to plant growth. For example, students had to design an experiment to test how different amounts of water or sunlight affect plant growth or create a poster to explain how plants grow from seeds to flowers.

Both activities and materials (including domain tests) were based on the General Studies curriculum of the school, which aimed to assess the student's knowledge and skills in various subjects. The process of co-designing the test with the teachers involved online meetings, training sessions, and iterative feedback. The teachers wrote a plan for the test, which was reviewed and revised by us until it met the quality standards. This way, we ensured that the test was aligned with the learning objectives and outcomes of the curriculum.

The process of implementation in Cycle 2 is presented in Figure 29. Before starting the courses, all students from both experimental and control groups attended a domain knowledge pre-quiz. The courses were conducted with two 60-minute sessions on Zoom with the m-Orchestrate app. All participating teachers mainly delivered teaching materials and conducted courses on the m-Orchestrate app. Only teachers in the experimental group used the LA tool to follow up and intervene in students' CSI process among different groups. Besides in-class activities, students also had some tasks as homework on the m-Orchestrate app between the two sessions. After finishing the second session, the participating students from all classes also attended a domain knowledge post-quiz, which was the same as the pre-quiz. Two semi-structured interviews were conducted in English to investigate the teachers from the experimental group on the newly developed bupaR features and each lasted 10 minutes.

4.3.2.3.1 Paricipants. In this cycle, four teachers (Teacher E1—a male teacher in the experimental group; Teacher E2—a female teacher in the experimental group; Teacher C1—a male teacher in the control group; and Teacher C2—a female teacher in the control group) and their Grade 4 students ($n = 100$) were involved. Teachers E1 & E2 and their two classes of students ($n = 50$, each class had $n = 25$) used the m-Orchestrate app with the refined LA tool as the experimental group. The other teachers (Teachers C1 & C2) and their two classes of students ($n = 50$, each class had $n = 25$) used the m-Orchestrate app but without the LA tool. All classes had 25 students in Grade 4 respectively. All students have their fixed inquiry groups according to existing arrangements by their teachers.

4.3.2.3.2 Data Collection. In Cycle 2, collected data includes (1) teachers' operation records on the LA tool on the m-Orchestrate app, (2)semi-structured teacher interviews, and (3) students' scores on domain knowledge pre- and post-quizzes.

Operation Records on the LA Tool. The log data of Teacher E1's operation on the LA tool were analyzed to identify when and how teachers orchestrate CSI learning activities using the LA tool. The use of bupaR features by Teacher E1 and E2 was also logged since the implementation of this cycle.

Teacher Interview. Two 10-minute semi-structured teacher interviews were conducted after this cycle to determine Teachers E1's & E2's perceptions of and experience with using the LA tool to orchestrate CSI, especially the newly added bupaR in this cycle. The interviews were audiotaped and conducted in English (see cleaned transcripts in Appendix E).

Student Domain Knowledge Pre- and Post-Quizzes. Students' scores on pre-quizzes and post-quizzes were conducted to examine their understanding of the domain knowledge related to "The Growth of Plants" (see Appendix F). The quiz is about the growth of plants, including nine items (i.e. "What substances are needed as raw materials for plant photosynthesis?"). The researcher designed the test and negotiated with the participating teachers to match their learning contents and objectives. There were 43 (from the experiment group) and 46 (from the control group) valid responses of student domain knowledge pre- and post-quiz collected in this cycle.

4.3.2.3.3 Data Analysis. The implementation in Cycle 2 focused on the newly added bupaR features of the refined LA tool for orchestration principles in terms of awareness, continuity, and flexibility, and their impact on teacher orchestration and student learning in an MLE. The data analysis methods were: (1) bupaR analysis, (2) inductive thematic analysis, and (3) independent and paired-sample t-tests. The following subsections describe each method briefly.

bupaR Analysis of Operation Records on the LA Tool. BupaR analysis is a process mining technique that can extract and analyze information from event logs. BupaR analysis was used to generate process maps and a process matrix that showed how teachers interacted with the LA tool's features in this cycle and how their interactions changed over time. The analysis also took the teachers' operation on pyBKT features into account to address the focus in Cycle 2. The results of the bupaR analysis could help understand teachers' adoption, usage, and perception of the LA tool, as well as their pedagogical strategies and challenges in facilitating students' CSI learning in an MLE.

Inductive Thematic Analysis of Teacher Interview. To analyze transcripts from online semi-structured interviews with teachers using the LA tool, an inductive thematic analysis approach was employed. This method involves a comprehensive analysis of the original contents in an interview. In this process, the transcripts were read carefully and categorized into themes and codes based on data patterns and emerging insights of feedback, specifically in Cycle 2, on their opinions towards the bupaR features.

Independent and Paired-Sample T-Tests of Student Domain Knowledge Pre- and Post-Quizzes. To examine the effects of the LA tool on students' learning outcomes, t-tests were conducted on the scores of students' pre- and post-quizzes in each cycle. The quizzes were designed to assess students' understanding of the course content and inquiry skills. SPSS software was used to compare the mean scores of the pre- and post-quizzes for each cycle.

4.3.2.3.4 Results.

Teacher E1's Operation Records on the LA Tool. In the current feature upgrade, the LA tool not only offered a more concise and lucid interface but also provided bupaR for instructors to make a more detailed process analysis for exploring behaviors. A new function, bupaR performed the real-time tracking of students' inquiry process. Upon the adoption of bupaR, participating Teacher E1 from Cycle 1 rapidly explored its functionality and employed it frequently throughout the instructional process, with its usage recorded 167 times (see Figure 36 and Figure 37).

While examining details remained the most frequently performed operation, occurring 359 times, it was usually followed by reviewing specific activity details in bupaR after scrutinizing students' learning particulars. These two functions were the most frequently used by Teacher E1 when operating learning tools. Interestingly, eight teacher resources were provided only after consulting bupaR, and after reviewing bupaR. Teacher E1 frequently commented on students' notes. However, they rarely utilized functions that provided resources or feedback, occurring only 33 and 22 times, respectively. The matrix chart in Figure 37 indicates that the frequency of activities focused on checking bupaR and other details rather than providing resources or feedback.

Figure 36

Process Map of Teacher E1's Operation in Cycle 2 by BupaR

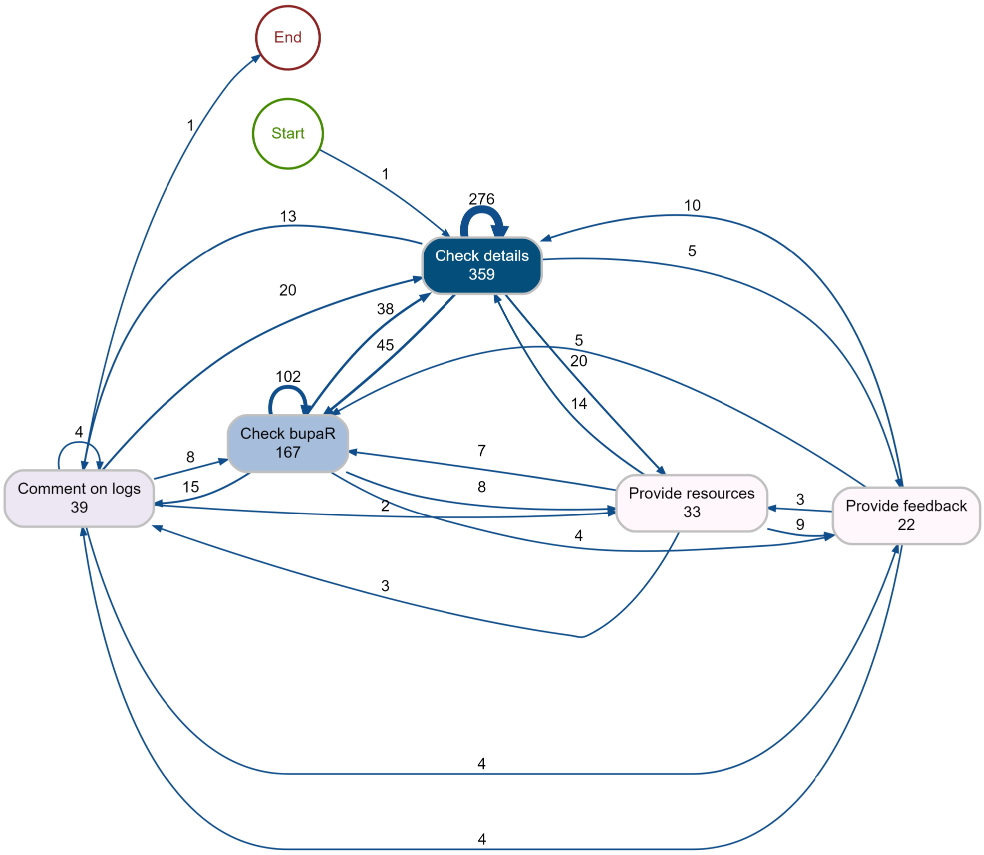
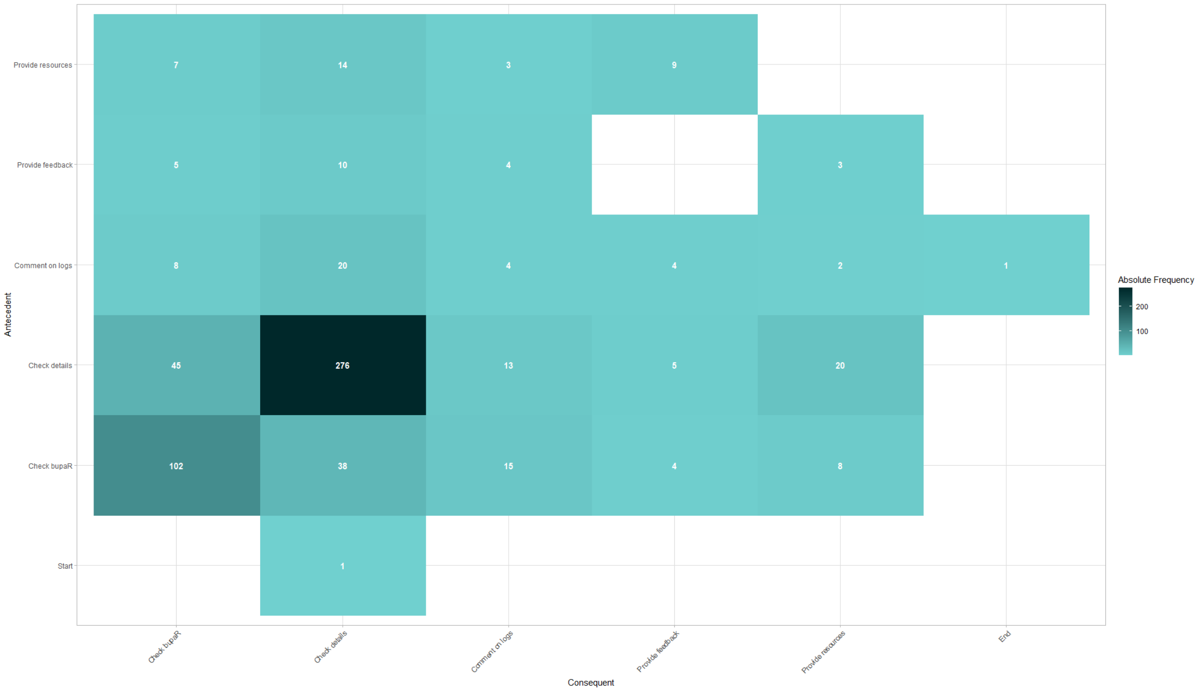


Figure 37

Process Matrix of Teacher E1's Operation in Cycle 2 by BupaR



Teacher E2's Operation Records on the LA Tool. Teacher E2 participated in this cycle. Upon using the LA tool, Teacher E2 demonstrated a greater tendency to check students' learning activity details, with a frequency of 232 times, and reviewed bupaR results with a frequency of 159 times, respectively (See Figure 38 and Figure 39. Similar to Teacher E1, Teacher E2 also provided students with a substantial number of teacher resources, totaling 66 cases, and commented on student activity records, totaling 68 cases. Depending on bupaR's results, the teacher also used them to review and evaluate student activities. After checking bupaR, Teacher E2 provided 12 resources and commented 21 times on logs, which was higher than Teacher E1. Consequently, more activity details garnered more teacher resource provision, and the provision of feedback and resources resulted in more interactions between teachers and students. In the matrix, the most frequent operation was checking details with a frequency of 131 times, which is nearly double the frequency of checking bupaR, at 68 times.

Figure 38

Process Map of Teacher E2 Operation's in Cycle 2 by BupaR

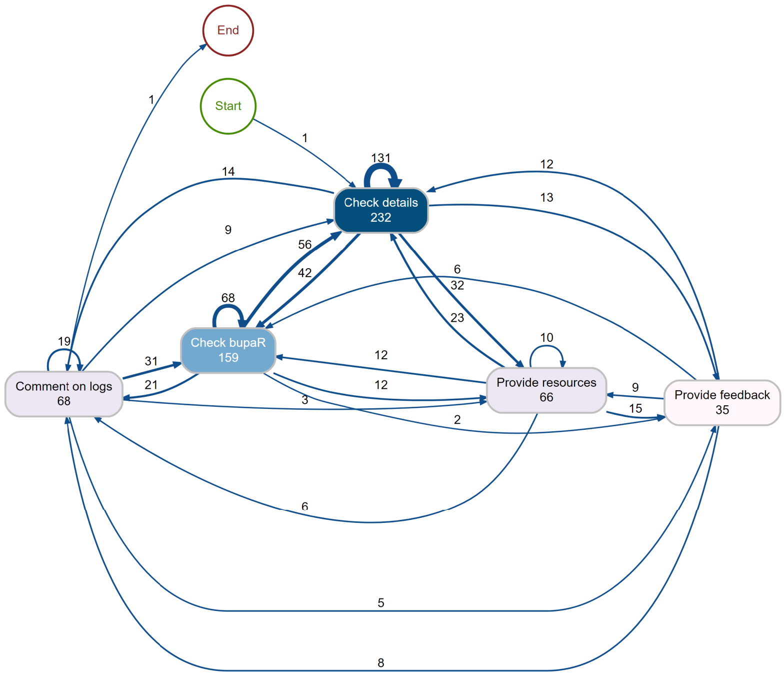
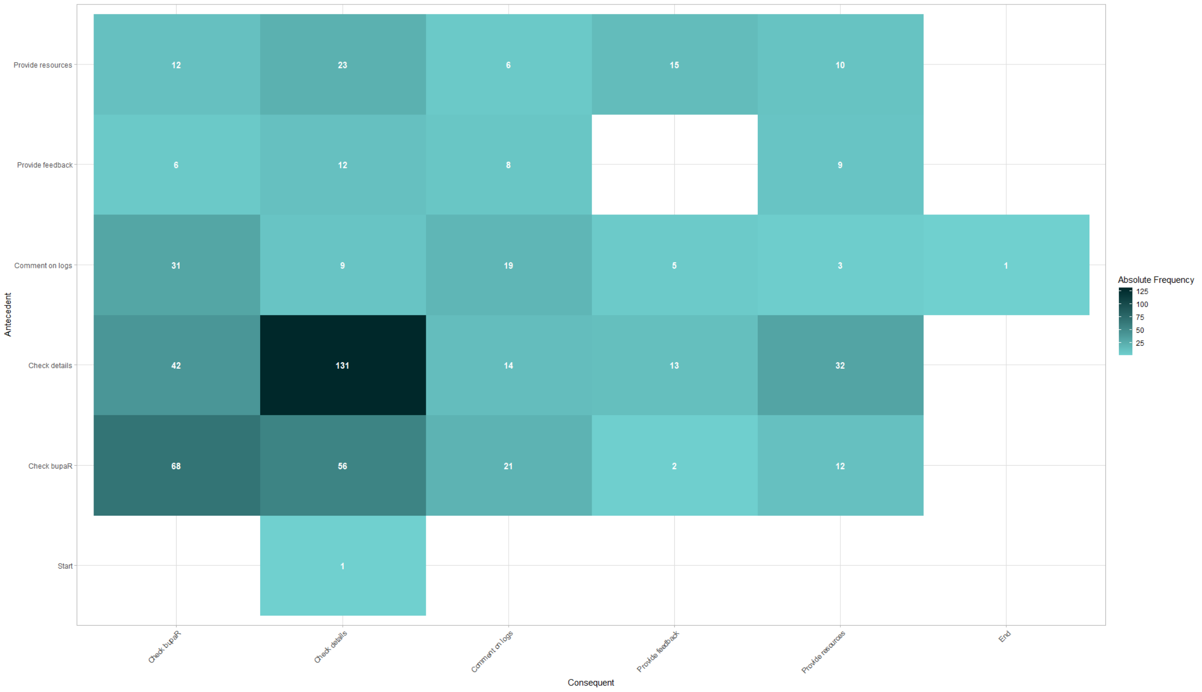


Figure 39

Process Matrix of Teacher E2's Operation in Cycle 2 by BupaR



Teacher Interviews. In the interview, two teachers (Teacher E1 & E2) discussed their experiences using the bupaR LA tool in their teaching. Their experience using bupaR was positive; however, they acknowledged the time and effort required to analyze the data and create personalized resources for students. The tool helped them track student progress and engagement, identify struggling students, and personalize learning experiences. Advantages included the accurate monitoring of student progress, data-driven decision making, and tailored instructional materials. Disadvantages include the risk of overreliance on data, privacy concerns, and technical challenges (see Table 13) Both teachers found bupaR useful for modifying teaching strategies on the fly and providing targeted resources and feedback. However, they emphasized the importance of balancing data with professional judgment and other assessment strategies.

Table 13

Thematic Analysis of Teacher Interview in Cycle 2

Theme	Sub-theme	Script
Awareness	Information obtained from the LA tool	"Regarding the information that bupaR could provide, it would depend on the specific parameters set for the tool. However, in general, bupaR is designed to help analyze data from various sources to identify patterns and insights related to student performance and engagement." (Teacher E1)
	Teaching experience using the LA tool	"Using bupaR in the M-Orchestrate app, I was able to notice information such as student progress and engagement, areas where students may be struggling, and individual student needs and learning preferences." (Teacher E2)
Continuity	Providing resources and feedback based on LA tool information	"Overall, while bupaR was a valuable tool in my teaching, it was not the sole source of information I used to provide resources and feedback to my students. Rather, I used a combination of data, observations, and professional judgment to make informed decisions about how to best support my students' learning." (Teacher E2)

Continued on the next page

Table 13

Thematic Analysis of Teacher Interview in Cycle 2 (cont.).

Theme	Sub-theme	Script
Flexibility	Modifying teaching strategies based on LA tool information	"Yes, the information from bupaR was very helpful in allowing me to modify my teaching strategies on the fly. One example was when I noticed that several students were struggling with a particular concept during a lesson. After checking the bupaR data, I saw that these students had consistently scored low on related practice exercises." (Teacher E1)
	Benefits of providing targeted resources and feedback based on different learning trajectories	"Yes, I agree. The bupaR tool provided insights into the different learning trajectories of the students, which helped me tailor my teaching approach to each group's individual needs." (Teacher E2)

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Student Domain Knowledge Quizzes. An independent t-test showed there was no significant difference between the total scores of pre-domain knowledge quizzes in experimental and control groups in Cycle 2 ($p > 0.05$), indicating there was no significant difference observed in students' prior science knowledge. An independent t-test was further conducted to examine the total scores of post-domain knowledge quizzes. The results showed that there was a significant difference between the total scores of post-domain tests in experimental and control groups in Cycle 2 ($p < 0.05$).

A paired-sample t-test was used to determine whether there was a statistically significant mean difference in pre- and post-domain tests in the experimental groups (the classes of Teacher E1 & E2) in Cycle 2. Table 14 conveys a significant difference between the total scores of the experimental group in Cycle 2's pre-domain test ($M = 70.50, SD = 4.25$) and post-domain test ($M = 82.36, SD = 4.67$), 95% CI $[9.24, 14.48]$, $t(43) = 9.42$, $p < 0.001$, suggesting that the learners' knowledge after the experimental group's advancement markedly improved after using m-Orchestrate in the collaborative inquiry in Cycle 2.

Table 14

Paired-Sample T-Test of Student Quiz Results from the Experimental Group in Cycle 2.

	Paired Differences							
				Mean diff. (95% CI)				
	Mean	SD	SEM	Lower	Upper	t	df	Sig. (2-tailed)
post-pre	11.86	5.91	1.26	9.24	14.48	9.42	43	.000***

Note. * : $p < 0.05$, ** : $p < 0.01$, *** : $p < 0.001$

A paired-sample t-test was used to determine whether there was a statistically significant mean difference in the pre- and post-domain quizzes in the control groups (the classes of

Teacher C1 & C2) in Cycle 2. Table 15 depicts a significant difference between the total scores of the experimental group in Cycle 2's pre-domain test ($M = 70.50, SD = 4.25$) and post-domain test ($M = 82.36, SD = 4.67$), 95% CI $[9.24, 14.48]$, $t(43) = 9.42$, $p > 0.05$, suggesting that the learners' knowledge of the experimental group's advancement was not significantly improved after using m-Orchestrate for collaborative inquiry in Cycle 2.

Table 15

Paired-Sample T-Test of Student Quiz Results from the Control Group in Cycle 2.

	Paired Differences							
				Mean diff. (95% CI)				
	Mean	SD	SEM	Lower	Upper	t	df	Sig. (2-tailed)
post-pre	0.92	3.32	1.81	-1.37	5.92	1.26	46	.54

Note. $^*: p < 0.05$, $^{**}: p < 0.01$, $^{***}: p < 0.001$

4.3.2.3.5 To address the research questions (RQs). For RQ1, the theory-led LA tool afforded teachers four main functions: checking details, commenting on notes, providing resources, and giving feedback. The most frequently used functions were checking details and reviewing bupaR results, which enabled teachers to monitor student engagement and performance, identify areas of difficulty, and provide targeted support based on different learning trajectories.

For RQ2, the theory-led LA tool positively impacted teacher orchestration in CSI. The tool helped teachers adjust their teaching approach, provide more resources and feedback, and make informed decisions about supporting student learning goals. However, there were also potential challenges associated with data overload and the limited scope of the tool. Teachers needed systems for analyzing and interpreting data and using the tool with other forms of assessment and evaluation.

For RQ3, the theory-led LA tool significantly impacted student learning performance in CSI. There was a significant difference between the pre- and post-domain knowledge quizzes in both experimental and control groups. The experimental group showed a significant improvement in domain knowledge after using the LA tool for CSI, while the control group showed no significant change.

4.3.2.4 Refinement. The main purpose of Cycle 2 was to develop and embed bupaR features in the LA tool to support teacher orchestration practices by going into more insights into student CSI processes. The dashboard was designed to provide teachers with real-time data on students' inquiry progress, engagement, performance, and collaboration, as well as advanced analytics using bupaR, a process mining tool. The dashboard also enabled teachers to intervene in students' inquiry activities by providing resources and feedback through the m-Orchestrate app.

The data collection and analysis methods used in Cycle 2 included operation records on the LA tool, teacher interviews, and student domain knowledge quizzes. These methods were appropriate for capturing quantitative and qualitative data on teacher orchestration practices and student learning outcomes. However, some limitations and challenges were also encountered.

The findings from Cycle 2 showed that the dashboard was generally well received by the participating teachers, who found it useful for monitoring and understanding students' inquiry processes, identifying struggling students, and personalizing learning experiences. The teachers also reported that the dashboard helped them modify their teaching strategies based on data-driven insights, such as providing targeted resources and feedback based on different learning trajectories. However, the teachers also acknowledged some challenges and limitations of using the dashboard, such as the time and effort required to analyze the data and create customized resources, the risk of overreliance on data, privacy concerns, and technical issues.

In Cycle 2, the first RQ explored the affordances of theory-led design interactive features of the LA tool for teacher orchestration of student CSI in an MLE. The newly embedded bupaR can help teachers gain more insights into students' CSI process. The frequency and patterns of teachers' operations on the LA tool were analyzed using BupaR. It shows that Teacher E1 & E2 used the newly developed bupaR features with the LA tool.

The RQ2 examined the impact of the LA tools on teachers' orchestration. Teachers E1 & E2, who used the LA tool in teaching a lesson on "The Growth of the Plants," were interviewed, and their operation records on the LA were collected. The inductive thematic analysis of the interview transcript identified some themes and sub-themes related to the teacher's perceptions, benefits, limitations, and flexibility of using the bupaR features. The results that Teachers E1 & E2 acknowledged the use of bupaR features for their orchestration practice.

The RQ3 investigated the impact of teacher orchestration supported by the theory-led LA tool on students' CSI performance. Student pre- and post-domain knowledge quizzes were conducted for students in experimental and control groups. Independent t-tests and paired-sample t-tests were performed to compare the scores of the quizzes. In Cycle 2, students in the experimental group (under Teacher E1's & E2's orchestration with the assistance of the LA tool) showed better performance than students in the control group (under Teacher C1's & C2's orchestration with the assistance of the LA tool).

The outcomes of Cycle 2 were consistent with the research questions and objectives of this action research project, which aimed to explore how LA can enhance teacher orchestration of CSI. The findings also aligned with the literature review and theoretical framework that informed this project, which suggested that LA can support teacher awareness, continuity, and flexibility in orchestrating complex learning scenarios (Prieto et al., 2015). Moreover, the findings contributed to the existing knowledge on LA for teacher orchestration by demonstrating how an interactive dashboard with advanced analytics can facilitate teacher decision making and intervention in CSI.

Based on these reflections, some changes or improvements were made in Cycle 3 to address the limitations and challenges identified in Cycle 2. The Python implementation of the Bayesian Knowledge Tracing (pyBKT) was adopted to recognize more relationships among students' CSI learning behaviors and the completion of inquiry phases. According to Anirudhan et al. (2021), some of the advantages of using pyBKT over other BKT implementations are:

- Accessibility: pyBKT is a Python-based library that can be easily installed in the LA tool's server and used with common data formats;
- Efficiency: pyBKT is computationally efficient and can handle large-scale datasets and model variants with fast runtime and low memory usage; and
- Flexibility: pyBKT can define and fit many BKT variants from the literature, as well as

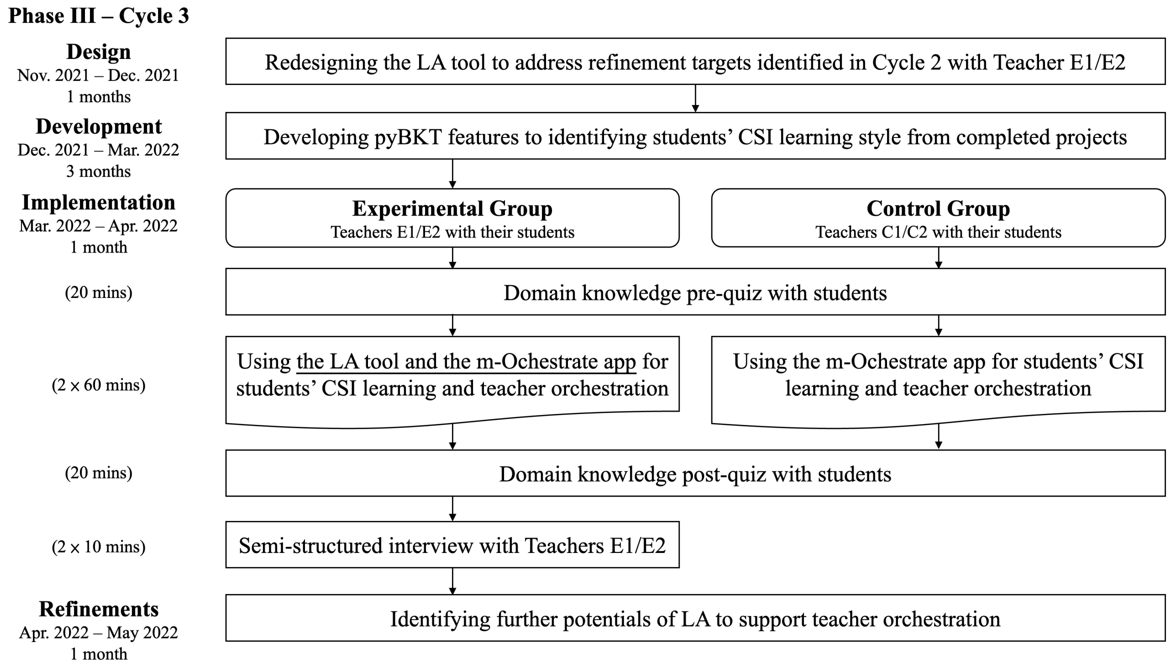
custom models with parameter fixing and extended features.

4.3.3 Cycle 3: Refinement and Implementation of the LA Tool with pyBKT for Orchestration Practice

In the third cycle, the pyBKT model was integrated into the LA tool as a component to recognize students' CSI styles from completed projects on the m-Orchestrate app. Cycle 3 of Phase III in the DBR aimed to refine the LA tool for teacher orchestration of CSI using LA. This cycle consists of four stages, including (1) redesign, (2) development, (3) implementation, and (4) refinement (see Figure 40). The redesign stage explains how the LA tool was refined with an advanced LA solution called Python implementation of the Bayesian Knowledge Tracing (pyBKT), which can recognize highly-related CSI behaviors with different inquiry phases. Similar to Cycle 2, the development stage demonstrates how the user interface of the orchestration viewport was enhanced to provide teachers with real-time data on students' inquiry progress, performance, engagement, and collaboration, as well as suggestions and feedback features more clearly. The implementation stage reports how the refined LA tool was used by two teachers and their students from the experimental group in an inquiry-based course, "Force, Motion, and Simple Machines," and how data was collected and analyzed using (1) teacher operation records, (2) teacher interviews, and (3) student domain knowledge pre- and post-quizzes. The refinement stage discussed how the findings showed that the further refined LA tool in Cycle 3 was helpful for teacher awareness, continuity, and flexibility in orchestrating CSI, especially with the CSI styles provided by the newly added pyBKT analysis based on students' behaviors, but also identified potentials can be addressed and realized in the future.

Figure 40

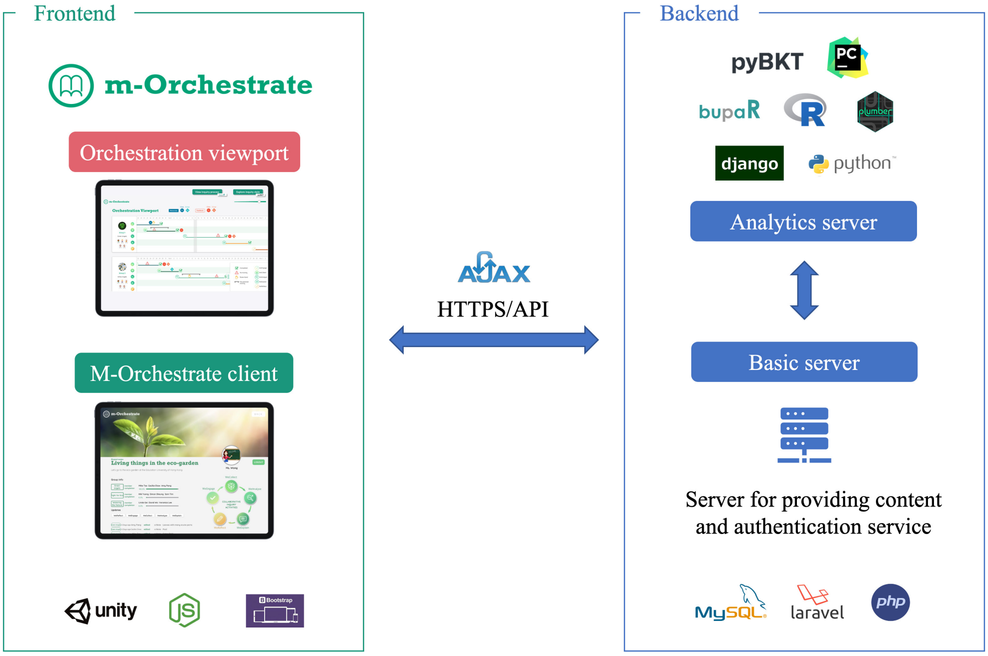
Research Activities in Cycle 3 of Phase III



4.3.3.1 Redesign. The redesign of the LA tool with an orchestration viewport used a more advanced data analysis approach in Cycle 3, pyBKT (Anirudhan et al., 2021), to analyze the data accumulated for previous inquiry projects to exploit more insights from their CSI activities. The system's framework is organized into two parts: the front end and the back end (see Figure 41). The front end is responsible for the user interface and interaction, such as the data visualization and interpretation components. The front end uses both the m-Orchestrate app and orchestration viewport supported by web technologies, such as HyperText Markup Language (HTML), CSS, and JavaScript. The back end is responsible for data management and processing, such as the data collection and analysis components. The back end uses various programming languages and tools, such as pyBKT in Python, bupaR in R, and SQL. The back end also includes PyCharm, a Python-based integrated development environment that supports the development and debugging of data analysis scripts and modules. As refined in Cycle 2, the server also adopts the Django and Plumber server in Python scripts to realize analytic tasks on the cloud side to solve the slow responses and low performance caused by the traditional Apache web server in PHP.

Figure 41

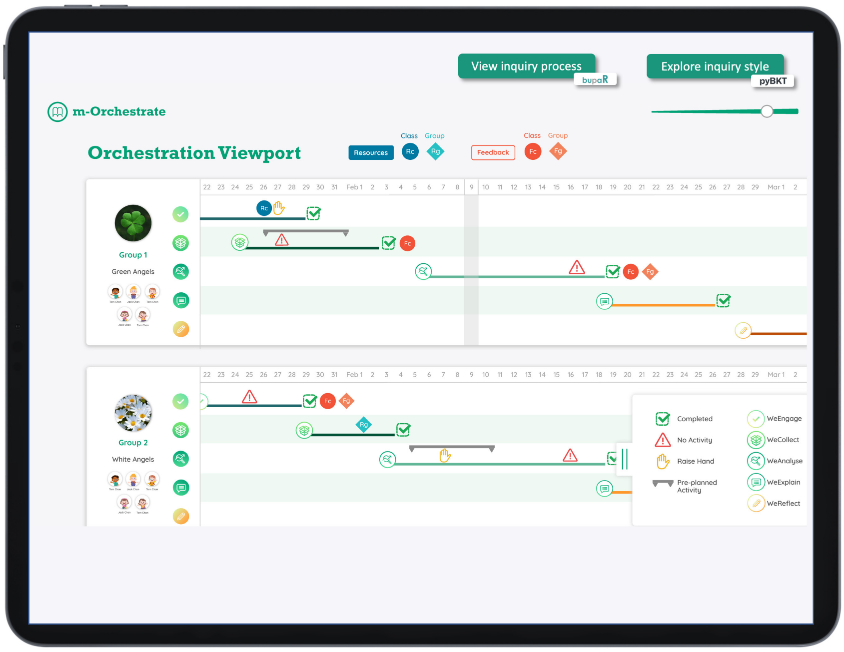
System Framework of the LA Tool Refined in Cycle 2



4.3.3.2 Development. An overview of the orchestration viewport interface in Cycle 3 is presented in Figure 42. The user interface demonstrates nested activities in bars and the timeline more explicitly than the design in Cycle 2. Group information and members are also listed in the right column of each panel. The nested activities indicate that the learner's progress and performance in different phases become lighter and thinner. The timeline also becomes thinner and is displayed in a "ruler" style to match the learner's activities and the teacher's pre-planned activities over time, correspondingly. Teachers can also provide resources and feedback to students, similar to the approaches in Cycle 2. The buttons to access advanced analytic results move to fixed positions on the right of the top bar so teachers can find them more easily.

Figure 42

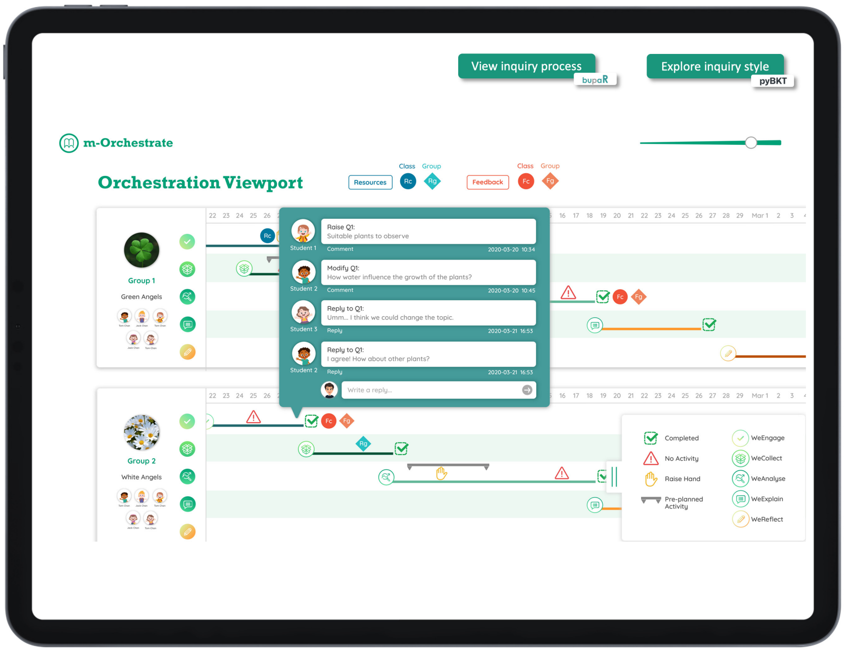
Orchestration Viewport Interface Design of LA Tool Refined in Cycle 2



Similar to the previous version of the LA tool design, the LA tool can still realize data collection and analysis, visualization, and representation using the m-Orchestrate app (see Figure 43). Furthermore, the visual elements and icon design have been revised slightly to be more user friendly and easier to distinguish. The orchestration viewport can better and more straightforwardly help teachers collect and interpret data from students' activities, monitor and understand the state of students' collaboration and inquiry, receive or provide feedback and guidance, and interact with students.

Figure 43

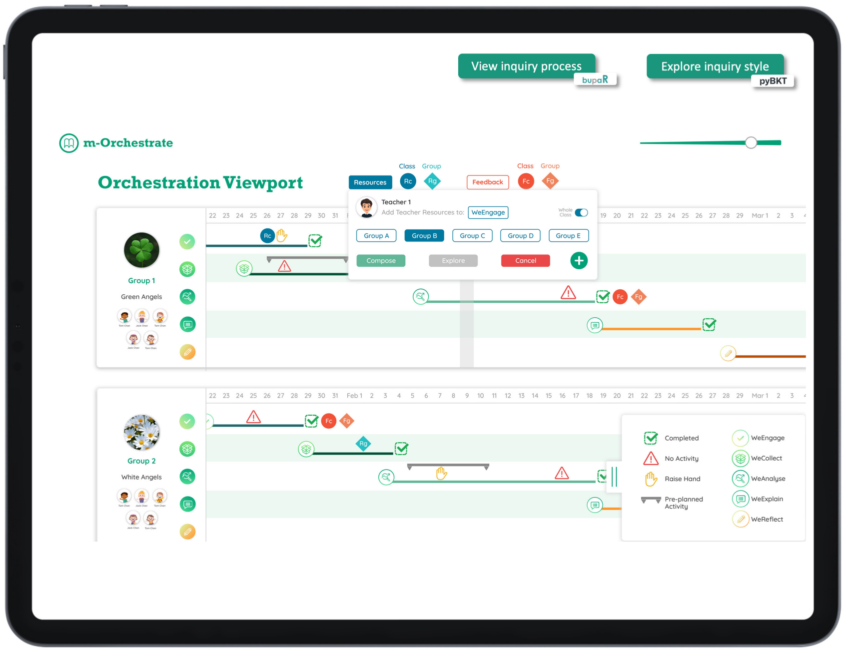
Refinements to the Checking of Inquiry Details in the LA Tool in Cycle 2



The LA tool still supports the teacher orchestration of the continuity aspect by seamlessly integrating data and interactive features to intervene based on the m-Orchestrate app in Cycle 3 (see Figure 44). The tool can collect and analyze log data on students' CSI activities from the m-Orchestrate app. The orchestration viewport can also coherently and consistently display data across inquiry phases and groups. It provides convenience for teachers to monitor and intervene in the classroom activity without disrupting the flow of students' CSI learning in multiple groups. The display of activities in the previous design of two cycles mixed various groups. The main purpose of this manner of design is to give teachers a way to view all groups at a glance. However, participating teachers are more likely to review records group by group. The newly designed interface organizes activity records by groups, making it less misleading for teachers to focus on each group's trajectory.

Figure 44

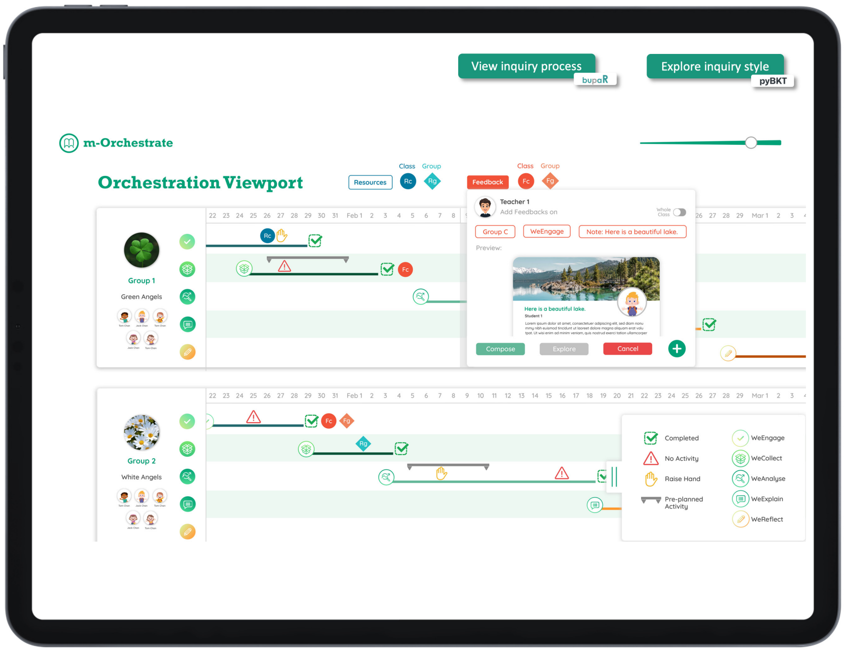
Refinements to the Provision of Resource Features in the LA Tool in Cycle 2



With the same design in Cycles 1 and 2, the orchestration viewport enables teachers to switch between different views and levels of granularity of the data, depending on their needs and goals (see Figure 45). Additionally, the gaps in nested activity bars can widen to help teachers distinguish activities among inquiry phases easily within a group. It can assist teachers in providing more flexible interventions according to the situations identified as needing further support. In this cycle, teachers can still access real-time bupaR data powered by the Plumber service to track and monitor students' inquiry status to inform just-in-time interventions.

Figure 45

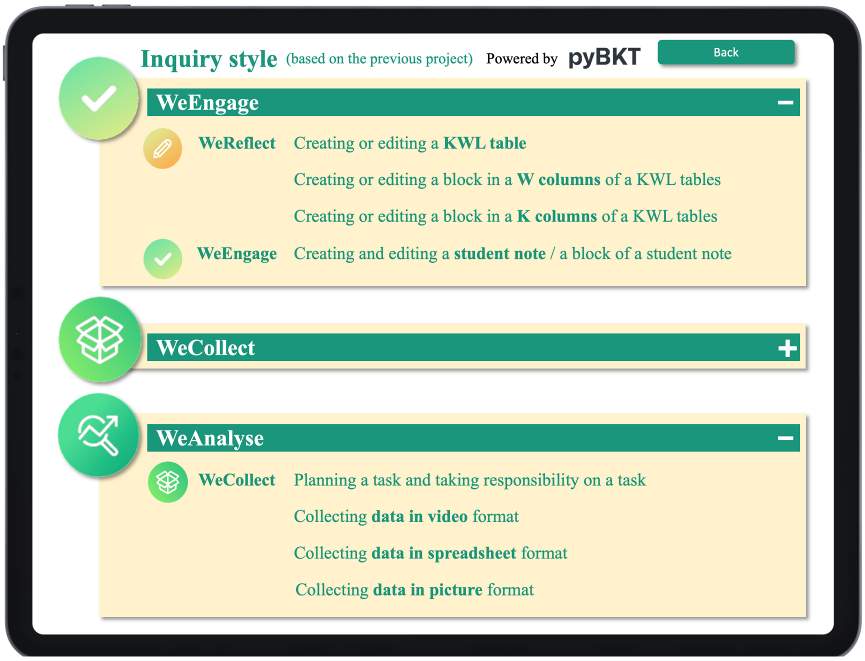
Refinements to the Provision of Feedback Features in the LA Tool in Cycle 2



Moreover, pyBKT is a Python library that implements the Bayesian Knowledge Tracing algorithm and its variants, which can estimate students' cognitive mastery from problem-solving sequences (see Figure 46) (Anirudhan et al., 2021). The image provided exemplifies the orchestration viewport of an LA tool that uses pyBKT to recognize the abilities of logged students' behaviors to predict the completion of CSI phases (see Python source codes in Appendix G).

Figure 46

Viewing the PyBKT Outputs of the LA Tool Refined in Cycle 2



4.3.3.3 Implementation. The implementation of the refined LA tool in Cycle 3 focused on the newly developed interfaces and pyBKT features to recognize students' CSI styles from completed projects. The course topic for all classes was "Force, Motion, and Simple Machines." The course was created using the m-Orchestrate app. The course allowed students to explore sub-topics related to the theme according to shared interests in their CSI learning groups. The teacher gave an overview of the topic and explained the main concepts of force, motion, and simple machines before students accessed the app to find multimedia resources, such as videos and animations, that illustrated how these concepts applied to real-world situations. The app also assigned activities that required students to work together to solve problems or create projects related to force, motion, and simple machines. For instance, students had to design a machine that could lift a heavy object or a vehicle that could move quickly on different terrains.

Both activities and materials (including domain tests) were based on the General Studies curriculum of the school, which aimed to assess the student's knowledge and skills in various subjects. The process of co-designing the test with the teachers involved online meetings, training sessions, and iterative feedback. The teachers wrote a plan for the test, which was reviewed and revised by us until it met the quality standards. This way, we ensured that the test was aligned with the learning objectives and outcomes of the curriculum.

The process of implementation in Cycle 3 is presented in Figure 40. Before starting the courses, all students from both experimental and control groups attended a domain knowledge pre-quiz. The courses were conducted with two 60-minute sessions on Zoom with the m-Orchestrate app. All participating teachers (Teachers E1, E2, C1, and C2) mainly delivered teaching materials and conducted in-class activities on the m-Orchestrate app. Only teachers from the experimental group used the LA tool to follow up and intervene in students' CSI process among different groups. Students also had some tasks as homework on the m-Orchestrate app between the two Zoom sessions. After finishing the second session, the participating students from all classes also attended a domain knowledge post-quiz, which was the same as the pre-quiz. Two semi-structured interviews were conducted in English to investigate the teachers from the experimental group on the newly developed pyBKT features and each lasted 10 minutes.

4.3.3.3.1 Paricipants. In this cycle, four teachers (Teacher E1—a male teacher in the experimental group; Teacher E2—a female teacher in the experimental group; Teacher C1—a male teacher in the control group; and Teacher C2—a female teacher in the control group) and their Grade 4 students ($n = 100$) were involved. Teachers E1 & E2 and their two classes of students ($n = 50$, each class had $n = 25$) used the m-Orchestrate app with the new LA tool as the experimental group. The other teachers (Teachers C1 & C2) and their two classes of students ($n = 50$, each class had $n = 25$) used the m-Orchestrate app but without the LA tool. All classes had 25 students in Grade 4 respectively. All students have their fixed inquiry groups according to existing arrangements by their teachers.

4.3.3.3.2 Data Collection. In Cycle 2, collected data includes (1) teachers' operation records on the LA tool on the m-Orchestrate app, (2)semi-structured teacher interviews, and (3) students' scores on domain knowledge pre- and post-quizzes.

Operation Records on the LA Tool. The log data of Teacher E1's operation on the LA tool were analyzed to identify when and how teachers orchestrate CSI learning activities using the LA tool. The use of bupaR features by Teacher E1 and E2 was also logged since the implementation of this cycle.

Teacher Interview. Two 10-minute semi-structured teacher interviews were conducted after this cycle to determine Teachers E1's & E2's perceptions of and experience with using the LA tool to orchestrate CSI, especially the newly added bupaR in this cycle. The interviews were audiotaped and conducted in English (see cleaned transcripts in Appendix H).

Student Domain Knowledge Pre- and Post-Quizzes. Students' scores on pre-quizzes and post-quizzes were conducted to examine their understanding of the domain knowledge related to "The Force, Motion, and Simple Machines" (see Appendix I). The quiz is about force, motion, and simple machines, including nine items (i.e. "Which of the following tools that apply the principle of the lever can help users save effort?"). The researcher designed the quiz and negotiated with the participating teachers to match their learning content and objectives. There were 43 (from the experiment group) and 46 (from the control group) valid responses of student domain knowledge pre- and post-quiz collected in this cycle.

4.3.3.3.3 Data Analysis. The implementation in Cycle 2 focused on the newly added bupaR features of the refined LA tool for orchestration principles in terms of awareness, continuity, and flexibility, and their impact on teacher orchestration and student learning in an MLE. The data analysis methods were: (1) bupaR analysis, (2) inductive thematic analysis, and (3) independent and paired-sample t-tests. The following subsections describe each method briefly.

bupaR Analysis of Operation Records on the LA Tool. BupaR analysis is a process mining technique that can extract and analyze information from event logs. BupaR analysis was used to generate process maps and a process matrix that showed how teachers interacted with the LA tool's features in this cycle and how their interactions changed over time. The analysis also took the teachers' operation on pyBKT features into account to address the focus in Cycle 3. The results of the bupaR analysis could help understand teachers' adoption, usage, and perception of the LA tool, as well as their pedagogical strategies and challenges in facilitating students' CSI learning in an MLE.

Inductive Thematic Analysis of Teacher Interview. To analyze transcripts from online semi-structured interviews with teachers using the LA tool, an inductive thematic analysis approach was employed. This method involves a comprehensive analysis of the original contents in an interview. In this process, the transcripts were read carefully and categorized into themes and codes based on data patterns and emerging insights of feedback, specifically in Cycle 2, on their opinions towards the pyBKT features.

Independent and Paired-Sample T-Tests of Student Domain Knowledge Pre- and Post-Quizzes. To examine the effects of the LA tool on students' learning outcomes, t-tests were conducted on the scores of students' pre- and post-quizzes in each cycle. The quizzes were designed to assess students' understanding of the course content and inquiry skills. SPSS software was used to compare the mean scores of the pre- and post-quizzes for each cycle.

4.3.3.3.4 Results.

Teacher E1's Operation Records on the LA Tool. In Cycle 3, Teacher E1 became acquainted with the LA tool and utilized bupaR, which was developed in the second cycle ($n = 169$) to a greater extent to examine activity details ($n = 357$) (see Figure 47 and Figure 48). Teacher E1 made considerable use of the newly added pyBKT, a novel function that identifies students' inquiry style from previous projects. Using pyBKT, bupaR was checked 357 times, followed by the checking of details 341 times. The interaction between these two functions was very frequent, higher than in Cycle 2. Forty-seven details were checked after consulting bupaR, while 56 bupaR were checked after examining the details. However, with the addition of the new functions in Cycles 2 and 3, the number of provided resources ($n = 6$) and feedback ($n = 19$) decreased. From the matrix chart, we can observe that the frequency of checking operations was much higher than providing operations.

Figure 47

Process Map of Teacher E1's Operation in Cycle 3 by BupaR

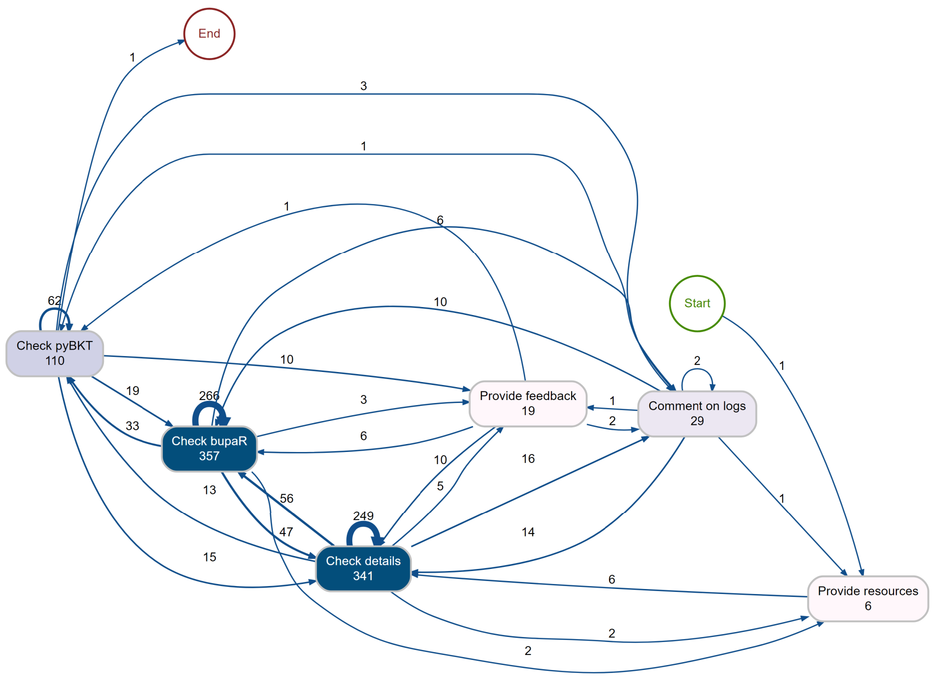
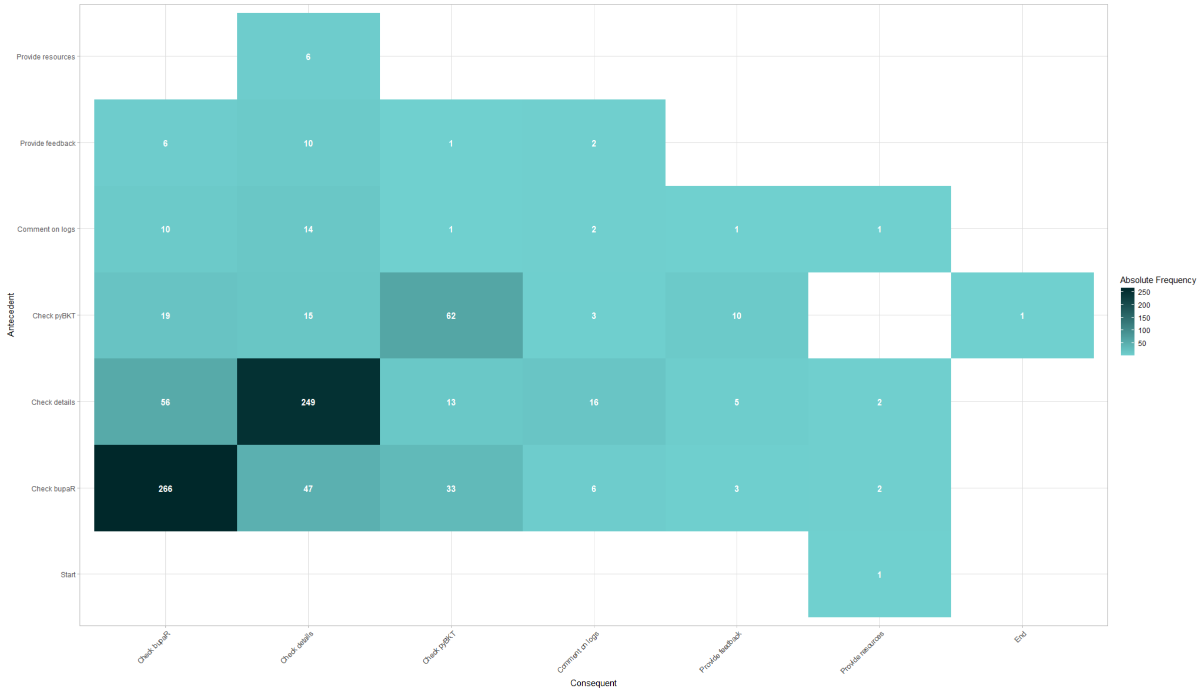


Figure 48

Process Matrix of Teacher E1's Operation in Cycle 3 by BupaR



Teacher E2's Operation Records on the LA Tool. When using the tool, Teacher E2 tended to observe students' activities more compared to the second cycle and focused on assessing specific student behaviors rather than providing comprehensive notes, such as teacher resources ($n = 4$) and feedback ($n = 45$) (see Figure 49 and Figure 50). In Cycle 3, Teacher E2 started to use bupaR results more for interventions rather than directly checking the activity details nested in bars. The frequency of operations on bupaR increased significantly from 159 to 229. By expanding the nested activity bars, positive attitudes were observed toward further-simplified interactions. Although teachers initially attempted more comprehensive feedback and resources for students, in the third cycle, the feedback and resources provided decreased significantly, with 45 and four occurrences, respectively. On the contrary, the comments on logs increased to 175, indicating that teachers more frequently provided short and direct comments on students' exploration behaviors. In this cycle, the new function, pyBKT, was checked 195 times, which had a positive interaction with checking bupaR and the details, and was higher than Teacher E1. The matrix indicated that the most frequent operation was checking bupaR, followed by commenting on logs, which diverged from other cycles. In addition, pyBKT was checked 91 times, which is higher than Teacher E1.

Figure 49

Process Map of Teacher E2's Operation in Cycle 3 by BupaR

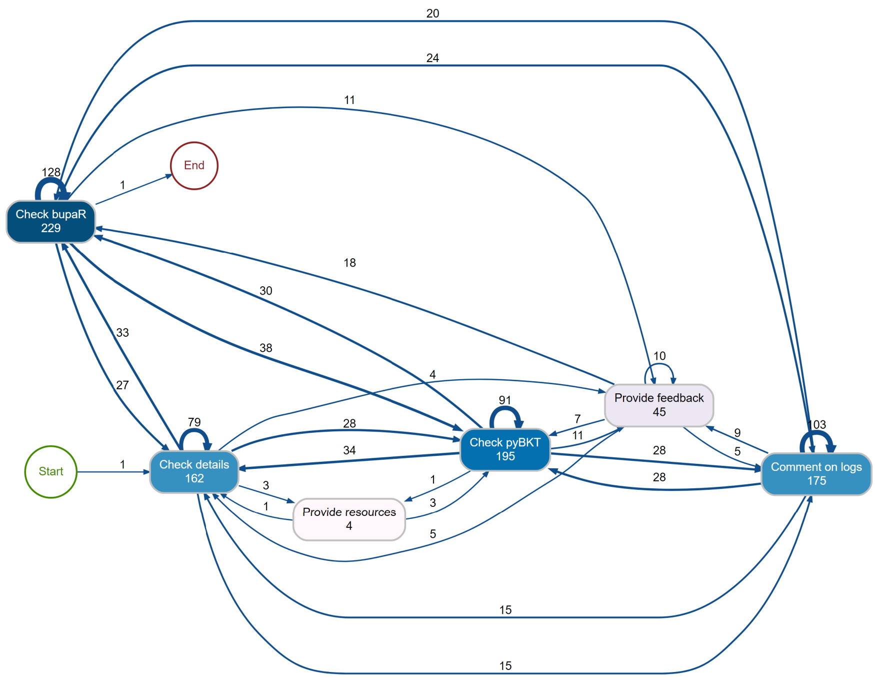
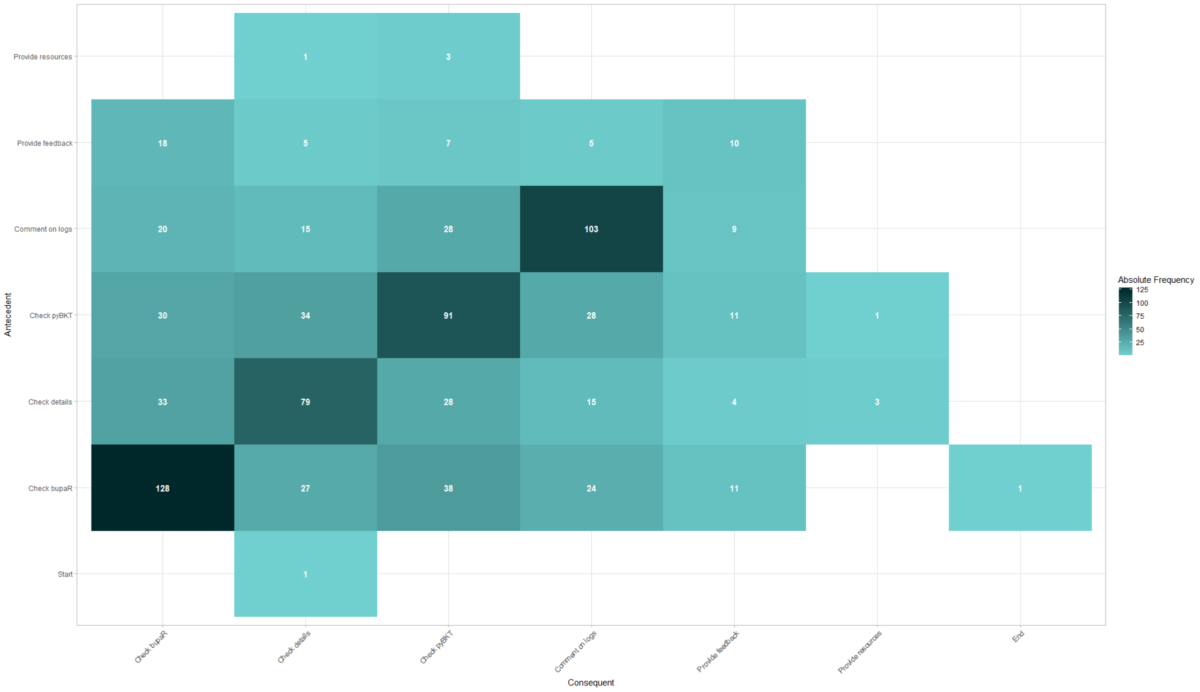


Figure 50

Process Matrix of Teacher E2's Operation in Cycle 3 by BupaR



Teachers' Interviews. Feedback from interviews of the two teachers (Teacher E1 & E2) from Cycle 3's experimental groups acknowledged that the pyBKT adopted in the m-Orchestrate app could provide valuable insights for teachers to understand more relevant inquiry-related behaviors to complete each inquiry phase. The feature provided by the pyBKT in the m-Orchestrate app can better facilitate teachers' orchestration practices. Teachers particularly used pyBKT to enhance their awareness, continuity, and flexibility in teaching (see Table 16).For example, Teacher E1 mentioned that pyBKT helped them identify struggling students, create personalized resources, and modify teaching strategies on the fly. Conversely, Teacher E2 found pyBKT useful for identifying struggling students; however, they did not rely on it to modify their teaching strategies, opting to use their own pedagogical knowledge and experience instead. Despite the benefits, the potential risks and challenges should be addressed, such as privacy concerns, data overload, an overreliance on technology, and maintaining a balanced and ethical approach when using these tools. Providing adequate training and support for teachers to use and integrate these tools into their teaching practices effectively is crucial to their successful implementation.

Specifically, from the teacher orchestration perspective, while the LA tool can provide valuable insights and support for teacher orchestration of CSI, it is not a substitute for teachers' professional judgment and expertise. Teachers must still interpret data and make informed decisions based on their knowledge of the subject, students' needs, and pedagogical goals. The tool's awareness, continuity, and flexibility features can facilitate teacher orchestration practices and improve the quality of student learning experiences. However, it is also important to consider potential risks and challenges, such as privacy concerns, data overload, and an overreliance on technology. The tool's impact on teachers' orchestration practice may vary depending on diverse factors, such as teachers' skills and attitudes, students' characteristics, and the learning context. Therefore, providing adequate training and support for teachers to effectively use the tool and integrate it into their teaching practices is crucial.

While the LA tool can enhance the efficiency and effectiveness of teacher orchestration, it may also change the nature of teacher–student interactions and the role of teachers in the learning process. Teachers must be mindful of the potential consequences and strive to maintain a balanced and ethical approach to using the tool. Both teachers found bupaR useful for modifying teaching strategies on the fly and providing targeted resources and feedback. However, they emphasized the importance of balancing data with their professional judgment and other assessment strategies.

Table 16

Thematic Analysis of Teachers' Interview in Cycle 3

Theme	Sub-theme	Script
Awareness	pyBKT's usefulness	"pyBKT provided me with information on how well students were able to grasp the different topics covered in the lesson." (Teacher E1)
		"One advantage is that pyBKT helped me identify areas where students were struggling and gave me insight into their misconceptions." (Teacher E1)
		"pyBKT helped me create personalized resources and activities for each student based on their learning trajectory." (Teacher E2)
Continuity	pyBKT usage	"I still found the tool useful in identifying areas where students were struggling or excelling. This helped me to tailor my teaching strategies accordingly and provide more targeted instruction for those students who needed extra help or challenges." (Teacher E1)

Continued on the next page

Table 16

Thematic Analysis of Teachers' Interview in Cycle 3 (cont.).

Theme	Sub-theme	Script
		"While the information was helpful in understanding each student's learning progress, I found that it did not always provide me with specific suggestions for how to modify my instruction." (Teacher E2)
		"I used the pyBKT data to inform my lesson planning, ensuring that I was covering the most important concepts and skills in a way that was accessible to students." (Teacher E2)
Flexibility	pyBKT's impact on teaching strategies	"pyBKT provided me with real-time information on how well each student understood the material, which allowed me to adjust my instruction accordingly." (Teacher E1)
		"Yes, I did provide resources and feedback to different groups based on their learning trajectories." (Teacher E1)
		"No, the information from pyBKT did not significantly help me modify my teaching strategies on the fly." (Teacher E2)

Continued on the next page

Table 16

Thematic Analysis of Teachers' Interview in Cycle 3 (cont.).

Theme	Sub-theme	Script
Challenges		"I found that sometimes the information provided by pyBKT was not entirely accurate or reflective of each student's understanding, which made it challenging to make informed decisions about how to modify my teaching strategies." (Teacher E2) "While I didn't provide individualized resources or feedback based on learning trajectories, I did use the data to make decisions that benefited the entire class." (Teacher E2)

The end of the table

Student Domain Knowledge Quizzes. An independent t-test showed there was a significant difference between the total scores of pre-domain knowledge quizzes in experimental and control groups in Cycle 3 ($p < 0.05$), indicating there was no significant difference observed in students' prior science knowledge. An independent t-test was further conducted to examine the total scores of post-domain knowledge quizzes. The results showed that there was a significant difference between the total scores of post-domain tests in experimental and control groups in Cycle 3 ($p < 0.05$).

A paired-sample t-test was used to determine whether there was a statistically significant mean distinction in the pre- and post-domain tests in the experimental groups (the classes of Teacher E1 & E2) in Cycle 3. Table 17 reveals a significant difference between the total scores of the experimental group in terms of the pre-domain test ($M = 70.68, SD = 4.82$) and post-domain test ($M = 86.32, SD = 5.46$), 95% CI $[13.99, 17.77]$, $t(43) = 15.36$, $p < 0.001$, suggesting learners' knowledge of the experimental group's advancement markedly improved after using m-Orchestrate in collaborative inquiry during Cycle 3.

Table 17

Paired-Sample T-Test of Student Quiz Results from the Experimental Group in Cycle 3.

	Paired Differences							
				Mean diff. (95% CI)				
	Mean	SD	SEM	Lower	Upper	t	df	Sig. (2-tailed)
post-pre	15.63	4.43	1.02	13.49	17.77	15.36	43	.000***

Note. $^{*}: p < 0.05$, $^{**}: p < 0.01$, $^{***}: p < 0.001$

Table 18 demonstrates no significant variation between the total scores of the control group (the classes of Teacher C1 & C2) in Cycle 3 in terms of the pre-domain test (M = 78.76, SD =

5.67) and post-domain test ($M = 81.04, SD = 6.45$), 95% CI of the mean difference $[-1.37, 5.92]$, $t(46) = 1.26$, $p > 0.05$, suggesting that learners' knowledge was not significantly improved after using m-Orchestrate in collaborative inquiry during Cycle 3.

Table 18

Paired-Sample T-Test of Student Quiz Results from the Control Group in Cycle 3.

	Paired Differences							
				Mean diff. (95% CI)				
	Mean	SD	SEM	Lower	Upper	t	df	Sig. (2-tailed)
post-pre	s2.28	3.38	1.72	-1.37	5.92	1.26	46	.214

Note. $^{*}: p < 0.05$, $^{**}: p < 0.01$, $^{***}: p < 0.001$

4.3.3.3.5 To address the research questions (RQs). For RQ1, the theory-led LA tool, which integrates bupaR and pyBKT, helps teachers monitor, assess, and support students' inquiry learning in each phase, as well as adjust their teaching strategies and resources based on the data and feedback from the tool.

For RQ2, the theory-led LA tool improves teacher orchestration by reducing their cognitive load and workload, enhancing their decision-making and intervention skills, facilitating their interactions with students, and aligning their instruction with the inquiry learning goals and theories. The teachers use bupaR and pyBKT to orchestrate student CSI.

For RQ3, the theory-led LA tool had a significant impact on student learning performance from the experimental group. The teacher orchestration supported by the theory-led LA tool enhances students' domain knowledge acquisition in CSI. The students in the experimental group outperformed those in the control group after using the tool.

4.3.3.4 Refinement. The impact of pyBKT features on teachers' orchestration practices in CSI is the focus of Cycle 3. The feature was added to the LA tool in Cycle 3 to give teachers more detailed and dynamic information on students' inquiry styles and learning trajectories. The operation records and the interviews showed that both teachers found the feature helpful for improving their awareness, continuity, and flexibility in orchestrating CSI. However, they also had some differences in their use and perception of the feature. Various factors may influence teachers' use and perception of pyBKT feature, and these factors should be considered when designing and implementing LA tools with pyBKT features for supporting teachers' orchestration practices in CSI.

The research activities in Cycle 3 examined the impact of pyBKT feature on students' domain knowledge acquisition in CSI. The pre- and post-domain quizzes showed that the experimental group that used the LA tool with pyBKT feature improved their domain knowledge acquisition more than the control group that used the LA tool without pyBKT feature. Two possible reasons for this finding are explained: one is that pyBKT feature enabled teachers to provide more timely and personalized guidance and feedback to students based on their inquiry styles and learning trajectories, and the other is that pyBKT feature increased students' awareness and reflection of their own inquiry processes and progress. These explanations are consistent with the literature, but more research is needed to explore the underlying mechanisms and mediating factors that influence the impact of pyBKT feature on students' domain knowledge acquisition in CSI.

Some limitations can be found in the version of LA tool refined and implemented in Cycle 3. The main limitation was the small sample size and the short duration of the intervention, which may limit the generalizability and validity of the findings. Future studies should involve more teachers and students from different contexts and backgrounds, and extend the duration of the intervention to examine the long-term effects of using LA tools with pyBKT features for supporting CSI. Another limitation was the lack of direct observation and measurement of students' inquiry behaviors and outcomes, which may limit the depth and richness of the data analysis.

Further studies should collect more qualitative and quantitative data from multiple sources to triangulate and validate the findings. A third limitation was the lack of evaluation of the usability and user satisfaction of the LA tool with pyBKT features from both teachers' and students' perspectives, which may limit the understanding of the user experience and acceptance of the tool. Future studies should conduct usability tests and user satisfaction surveys to assess the design quality and user feedback of the tool.

4.4 Phase IV—Reflection for Further Implementation of the LA Tool

Phase IV focused on making reflections on the affordances of the theory-led Learning Analytics (LA) tool for the teacher orchestration of Collaborative Science Inquiry (CSI) in a Mobile Learning Environment (MLE). The process of the Design-Based Research (DBR) was summarized. The study found that the theory-led LA tool offered several affordances for the teacher orchestration of CSI. It provided real-time data monitoring and visualization, supplied adaptive feedback and guidance, fostered collaboration and communication, supported data-driven decision making, and facilitated reflective practice and pedagogical improvement. In addition, the integration of the theory-led LA tool had a positive impact on the teacher orchestration of CSI. It enhanced teachers' understanding of student learning, enabled personalized feedback and interventions, supported at-risk students, allowed class-wide progress monitoring, and promoted reflective practice.

4.4.1 Summary of the Design-Based Research Process

In this section, the DBR (Collins et al., 2004) was adopted to integrate the LA tool into teacher orchestration of student CSI in an MLE. The five features of this DBR are (1) theory-led redesign and development of the m-Orchestrate app, (2) theory-led design and redesign of the LA tool, (3) addressing needs and issues related to the LA tool from practice, (4) co-design the LA tool with teachers, and (5) progressive refinements of the LA tool. Firstly, Before or during implementation, the design and redesign of the LA tool should be theory-led, meaning that it should be based on a clear conceptualization of how LA can enhance learning and teaching in specific contexts and domains. Secondly, LA tool implementation should address needs and issues from practice, meaning that it should identify authentic problems or challenges that learners, teachers, or educational institutions face and design solutions to solve or improve them. Thirdly, LA tool implementation should involve co-design, meaning that it should engage multiple stakeholders in the process of designing, implementing, and evaluating LA tools. Forthly, LA tool implementation should involve progressive refinements, meaning that it should iterate over multiple cycles of design, implementation, and evaluation to improve LA tools based on empirical evidence.

4.4.1.1 Redesign of the M-Orchestrate App. The newly developed m-Orchestrate app that was improved and enhanced in Phase I has the potential to support a LA tool that is based on a theoretical framework. The pilot study on the m-Orchestrate web platform (Song et al., 2019) found the platform's features and interface designed by following conventional user habits could not address the teaching and learning needs of CSI in an MLE. Feedback from teachers mainly pointed out that the ability of the app should respond to relevant needs in learning and teaching and let them know what they could facilitate in students' CSI journey.

Theory-led design (Kelly et al., 2015) acted as an approach to developing the m-Orchestrate app that is based on first principles derived from educational theories. Using educational theories can lead to an innovative design of a technical solution. Aligning with educational theories should not just label or categorize materials in an existing schema (McKenney & Mor, 2015). An effective educational application is expected to provide relevant features and interactions that can help achieve the goals and ideal actions allocated in educational theories (Cao & Song, 2019). The m-Orchestrate app has been developed to support CSL through its five phases: WeEngage, WeCollect, WeAnalyse, WeExplain, and WeReflect (Song et al., 2022). These stages were designed to provide a structured framework for CSL and to improve the learning experience for students.

In the WeEngage phase, students are tasked with generating inquiry-related questions relevant to a specific topic. The m-Orchestrate app provides a platform for students to engage in meaningful discussions, drawing upon external information and evidence to formulate insightful inquiry questions. The observed group demonstrated a high level of engagement, with all members actively participating in the discussions and proposing relevant questions. Moreover, the app fosters a sense of collective decision making, ensuring that all group members are involved in the final selection of inquiry questions. This collaborative approach encourages critical thinking and enables students to develop a deeper understanding of the subject matter (Bao et al., 2021).

The WeCollect phase is vital for students to plan and execute their investigative tasks. The

M-Orchestrate app offers a comprehensive toolkit that enables students to allocate roles, assign tasks, and collect data in various multimedia formats. In the observed group, the app facilitated effective task allocation, with the group leader assuming responsibility for organizing and clarifying the assigned roles. Furthermore, the app encourages students to monitor their progress and adhere to the planned timeline, ensuring successful data collection in multimedia formats. This systematic approach enhances students' organizational skills, fosters a sense of accountability, and promotes effective collaboration within the group.

The WeAnalyse phase focuses on data analysis, and the m-Orchestrate app provides students with the necessary tools and resources to analyze the collected data effectively. The app supports multiple modes of data analysis, accommodating diverse formats, such as text, images, videos, and spreadsheets. By utilizing these embedded tools, students can collaboratively discuss and implement appropriate analytical approaches, advancing their critical thinking abilities and data interpretation skills. The app's intuitive interface and user-friendly features empower students to engage with the data analysis process, facilitating a deeper understanding of scientific concepts and fostering collaborative problem-solving skills.

The WeExplain phase focuses on synthesizing the data collected and analyzed, culminating in group presentations. The M-Orchestrate app enables students to collaborate in creating visually appealing presentations that effectively communicate their group's investigation findings. While not all students may be directly involved in slide preparation, the app ensures that every student actively participates in presenting the group's work. By incorporating the data collected and analyzed on the app, as well as supplementary visual aids from the Internet, students can deliver comprehensive and engaging presentations. This stage not only enhances their presentation skills but also reinforces their understanding of the scientific concepts explored throughout the CSL process.

The WeReflect phase promotes metacognitive awareness and encourages students to evaluate the resolution of their inquiry-related questions while reflecting on the overall investigative process. The m-Orchestrate app facilitates this reflection by integrating a KWL table. This tool prompts students to review their initial knowledge, articulate their learning objectives, and summarize their findings after completing the activity. Engaging in reflective practices allows students to consolidate their understanding, identify areas for improvement, and develop a deeper appreciation for the scientific inquiry process.

Thus, the newly developed and featured m-Orchestrate app in Phase I has the feasibility to enable a theory-led LA tool embedded in it. Through specifically designed features for CSI learning and orchestration needs (Du et al., 2021), such as online discussions, peer feedback, and shared resources, this affordance encourages collaborative inquiry and knowledge co-construction (Bell et al., 2010; Minner et al., 2010). Students can share their findings, insights, and questions, sending or receiving feedback and suggestions (Wertsch, 1985) to or from peers and their teachers. This collaborative environment nurtures a sense of community, fosters peer learning, and enhances students' understanding of complex concepts through active engagement and discussion (Savery, 2015).

4.4.1.2 Theory-Led Design of the Learning Analytics Tool. DBR methodology aims to bridge the gap between theory and practice in education by designing, implementing, and evaluating interventions informed by learning theories to address real-world problems (Collins et al., 2004). LA involves the measurement, collection, analysis, and reporting of learner data and contextual information to understand and optimize learning (Siemens et al., 2011). LA tools are information systems that leverage LA to support learning and teaching (Nguyen et al., 2022). In this section, we discuss the implications of DBR for LA tool implementation from four perspectives: theory-led design and redesign, the addressing of needs and issues from practice, co-design, and progressive refinements.

This design of the LA tool is characterized by a theory-led approach (Kelly et al., 2015), which involves using existing or emerging learning theories to guide intervention design and explain outcomes (Collins et al., 2004). Similarly, the implementation of the LA tool should be theory-led, that is, based on a clear conceptualization of how LA can enhance learning and teaching in specific contexts and domains. For example, Nguyen et al. (2022) developed a set of design principles for LA information systems based on the literature on self-regulated learning, feedback, motivation, and engagement. By being theory-led, LA tool implementation ensures that design decisions align with the learning goals and pedagogical approaches of the courses or programs in which they are used (Aldowah et al., 2019). Moreover, being theory-led helps generate new insights and hypotheses (Pelánek, 2020) about the nature of learning in online environments, which can inform further research and development.

4.4.1.3 Addressing Needs and Issues Related to the Learning Analytics Tool from Practice. Another feature of DBR is that it addresses needs and issues from practice, meaning that it identifies authentic problems or challenges that learners, teachers, or educational institutions face and designs interventions to solve or improve them (Wang et al., 2020). Similarly, LA tool implementation should address needs and issues from practice and be responsive to the specific needs and expectations of the stakeholders who will use or benefit from them (Bao et al., 2021; van Leeuwen, 2015). By addressing needs and issues from practice, LA tool implementation ensures that design decisions are relevant and useful for the intended users and contexts (Hernandez-Lara et al., 2019). Moreover, addressing needs and issues from practice helps foster a culture of evidence-based decision making and improvement in education. The study conducted by VanLehn et al. (2021) also revealed that the LA tool developed and implemented was more accepted by experienced teachers who could orchestrate the CSI learning activities and intervene when necessary. However, it was also noted that technology-enhanced orchestration may not be sufficient to improve CSI learning in the context of an MLE, and further research is required to design and implement such systems effectively.

4.4.1.4 Co-Design the Learning Analytics Tool with Teachers. The DBR involves co-design, engaging multiple stakeholders in the process of designing, implementing, and evaluating interventions (Penuel et al., 2011). Similarly, LA tool implementation should involve co-design, involving learners, teachers, administrators, developers, and researchers as active participants in the development and use of LA tools. For example, Nguyen et al. (2022) involved instructors and students as co-designers in an iterative process of prototyping, testing, and refining LA dashboards. By involving co-design, LA tool implementation ensures that design decisions are informed by diverse perspectives and feedback from different users and experts (Schwendimann et al., 2017). Moreover, involving co-design helps increase the ownership and acceptance of LA tools among stakeholders. Throughout the DBR process, close contact with participating teachers allowed their active involvement in the design, development, and refinement of the LA tool (Collins et al., 2004). The teachers not only served as users of the developed LA tool but also provided firsthand comments for improvements during the iterative cycles. Their input provided valuable insights into their teaching needs, which were addressed through optimized analysis, visualization, and interaction strategies.

4.4.1.5 Progressive Refinements of the Learning Analytics Tool. DBR involves progressive refinements, iterating over multiple cycles of design, implementation, and evaluation to improve interventions based on empirical evidence (Collins et al., 2004). Similarly, LA tool implementation should involve progressive refinements, continuous monitoring, assessing, and improving the functionality and effectiveness of LA tools based on data collected from their use. For example, Nguyen et al. (2022) conducted four cycles of evaluation with different courses to examine the usability and usefulness of LA dashboards.

In this study, the refinements in Cycle 1 revealed the affordances, impact, and limitations of a theory-led design LA tool for teacher orchestration of student CSI in an MLE. They also suggested the need for Cycle 2, which focused on developing an interactive dashboard with bupaR to visualize students' CSI processes and support teachers' decision making. The advantages of bupaR over other analysis approaches for process mining were explained.

By developing and embedding bupaR features in the LA tool, the refinements in Cycle 2 supported teacher orchestration of student CSI processes and revealed the findings. The challenges and limitations of using the dashboard, such as data analysis, privacy, and technical issues, were also identified. It indicated to design and develop pyBKT features to recognize more relationships among students' CSI learning behaviors and the completion of inquiry phases in Cycle 3. The benefits of pyBKT over other BKT implementations, such as accessibility, efficiency, and flexibility, were acknowledged as a solution for further understanding students' CSI behaviors.

Refinements in Cycle 3 focused on pyBKT features to the LA tool to support teachers and students in CSI. It shows how the features helped teachers improve their orchestration practices, and how they enhanced students' domain knowledge acquisition. It also discussed some limitations of the study, such as small sample size, short intervention duration, lack of direct observation and measurement of students' inquiry behaviors and outcomes, and lack of usability and user satisfaction evaluation to build a convincing analysis of student CSI behaviors.

By involving progressive refinements, LA tool implementation ensures that design decisions are validated by rigorous methods and results. Moreover, progressive refinements help adapt LA tools to changing needs and contexts over time.

4.4.2 Affordances of the Refined Theory-Led Learning Analytics Tool

From the three cycles of implementation in the DBR, the theory-led LA tool provided valuable affordances for teachers to effectively orchestrate CSI activities, leading to better student understanding, and performance, evidenced by the increased domain test scores. The findings contributed to our understanding of the role of LA tools in supporting teacher orchestration and optimizing student learning outcomes in collaborative inquiry contexts.

Three types of affordances of the LA tool include (1) the affordance of the LA tool with interactive features for just-in-time orchestration (supporting students' CSI learning in five phases on the m-Orchestrate app); (2) the affordance of the LA tool with Business Process Analytics in R (bupaR) features for orchestration practice (visualizing students CSI learning process in detail and into insights); and (3) the affordance of the LA tool with Python implementation of the Bayesian Knowledge Tracing (pyBKT) features for orchestration practice (identifying highly-related CSI behaviors with the completion of an inquiry phase).

4.4.2.1 Affordances of the LA Tool for Awareness. The affordances for awareness include nesting students' inquiry activities, tracking the status of inquiry-based learning activities, showing the "Raise Hand" icon, presenting pre-planned schedules, and providing a zoom slider and group filter.

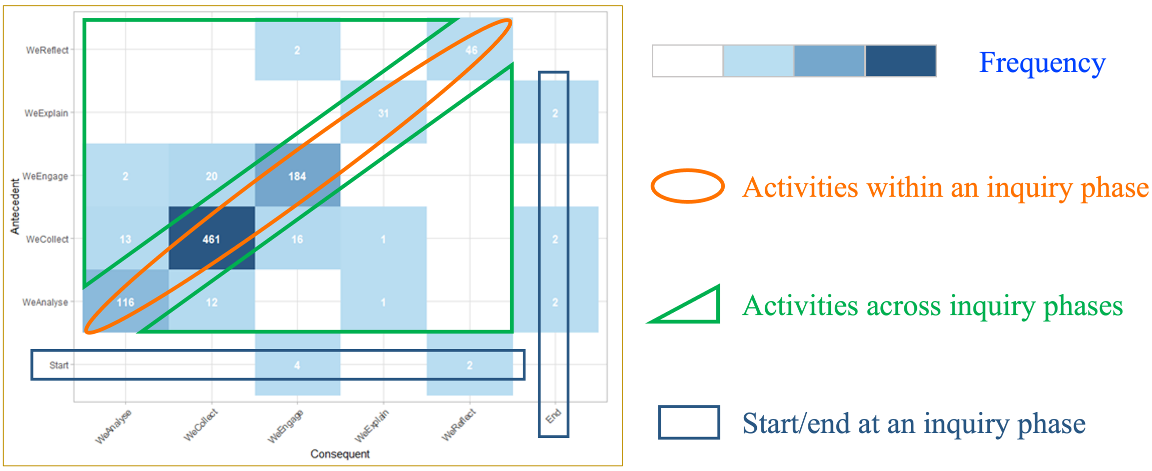
- Nesting students' inquiry activities (in concentrated time periods) within color bars for teachers to grasp the inquiry status among groups at a glance;
- Popping up a modal window when teachers click the nested bars to view students' inquiry activities in detail;
- Tracking the status of inquiry-based learning activities in distinct phases, such as "completed" or "idle" for a certain period of time, which are easy to follow up in a timely fashion;
- Showing the "Raise Hand" icon at specific time and inquiry phases after students click on the interface of the m-Orchestrate app to request the teacher's help;
- Presenting pre-planned schedules as gray bars at the top of each inquiry phase row to compare the real-time progress of assorted groups on the same interface;
- Providing a zoom slider and group filter to focus on specific inquiry phases and groups;
- Demonstrating the status and activities of students' inquiries holistically to support pedagogical actions based on the different learning trajectories among groups.
- Monitoring students' progress and performance by bupaR via tracking students' activities, interactions, and outcomes in real time or retrospectively; and
- Knowing student CSI behaviors from a specific group with higher predictabilities to the

completion of inquiry phases according to previous projects.

For example, by using bupaR features, teachers could make evidence-based decisions about how to improve the course and enhance students' performance (see Figure 51).

Figure 51

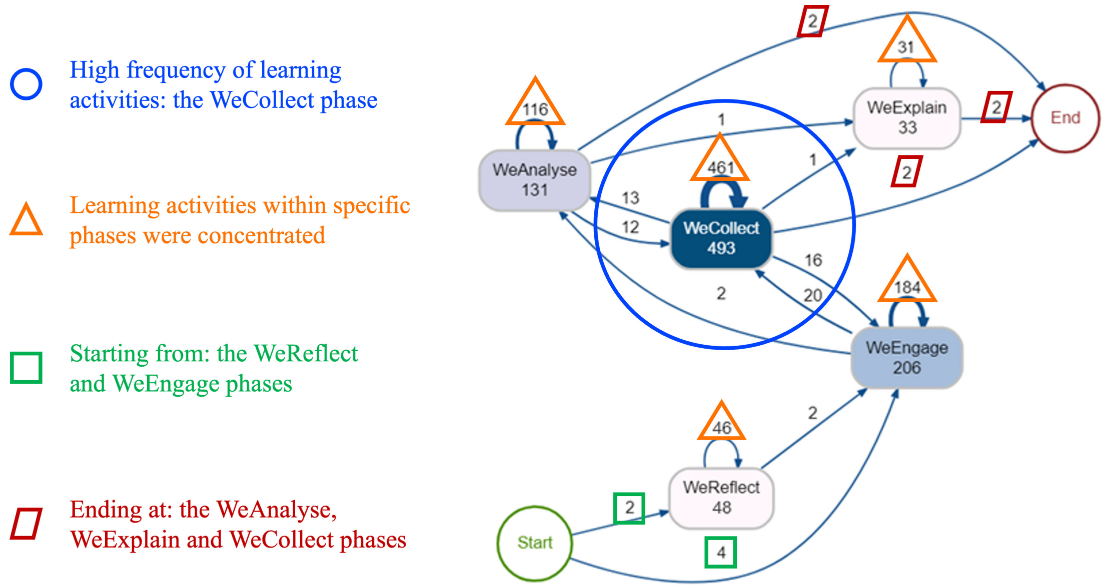
An Example of a Process Matrix of Students' CSI Behaviors Output by BupaR



A process map in bupaR is a direct-flow graph, where a node represents each distinct activity. The node relationships between activities are shown by arrows between nodes (see Figure 52). The bupaR process map in the image link shows the absolute frequency of transitions between students' CSI learning activities in a group inquiry process with Start and End. The nodes are labeled with the activity names and the number of occurrences. The edges are labeled with the number of times a source target activity directly followed a source activity.

Figure 52

An Example of a Process Map of Students' CSI Behavior Outputs by BupaR



4.4.2.2 Affordances of the LA Tool for Continuity. The affordances for continuity include releasing resources, giving feedback at both class and group levels, and providing relevant interventions with continuity.

- Releasing "Resources" and give "Feedback" by clicking on the two navigation bars in the specific inquiry phase and activity;
- Reducing disturbing by irrelevant interventions towards CSI processes among different groups;
- Providing resources and guidance according to bupaR results to identify students' specific needs, strengths, and weaknesses in their own group CSI process, as well as opportunities for improvement; and

- Guiding students from a specific group to conduct CSI activities with higher abilities to predict the completion of inquiry phases via pyBKT for keeping their continuous contribution to the current project.

4.4.2.3 Affordances of the LA Tool for Flexibility. The affordances for flexibility include enabling teachers to provide interventions both in advance and on the fly, providing related resources and feedback to students on different social levels, and displaying the previous interventions conducted through the LA tool.

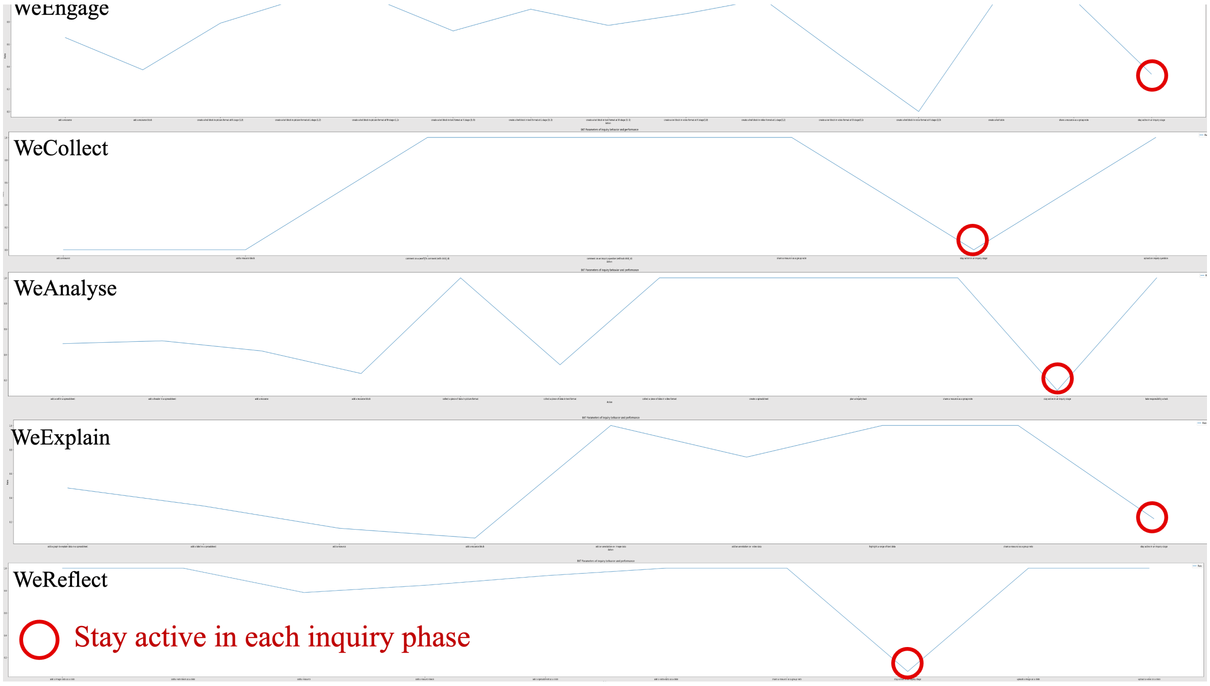
- Enabling teachers to release “resources” and “feedback” as just-in-time interventions on the corresponding occasions and contents to respond to students’ inquiry needs;
- Providing related resources and feedback to students on different social levels, namely, individual, group, and class;
- Displaying previous interventions conducted through the LA tool for teachers to consider further pedagogical strategies;
- Adapting learning scenarios and strategies by evaluating the effectiveness and efficiency of group CSI progress in real time according to bupaR results; and
- Selecting CSI activities with higher predictabilities to completion of ongoing phases based on pyBKT results according to different groups.

For example, pyBKT involved since Cycle 3 of Phase III in this study and provided valuable insights into modeling students’ CSI behaviors and their predictabilities on the completion status of phases. The pyBKT features indicated highly-related student CSI behaviors among different groups. The results can be pieces of evidence for shaping flexible teacher orchestration of student CSI in an MLE. One group’s results are presented below to demonstrate what actionable information could be provided by the pyBKT features.

Low Predictability of the Log Item "Stay Active in Each Inquiry Phase". Figure 53 presents an overview of a pyBKT model applied to the WeEngage, WeCollect, WeAnalyse, WeExplain, and WeReflect phases to relay the predictability of students' operation logs in m-Orchestrate to complete the corresponding inquiry phase. "Stay active in each inquiry phase" refers to students entering the main interface of an inquiry phase. This type of logged behavior showed low predictability on the completion of each inquiry phase. Thus, we can observe that most clicked-on logs are not very informative for understanding students' learning performance. The findings suggest that general action data (visiting/clicking on events in inquiry phases) are less useful for predicting group performance in CSI learning. Log data analyzed on the LA tool aligning with theories (e.g., raising inquiry questions, collecting data) can better predict group performance in CSI learning.

Figure 53

Low Predictability of the Log Item "Stay Active in Each Inquiry Phase"



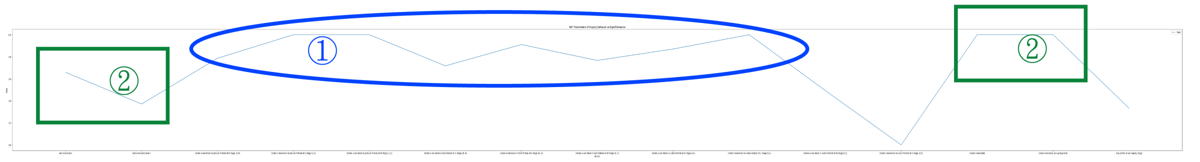
Log Items' Ability to Predict the Completion of the WeEngage Phase. Students' inquiry behaviors on the m-Orchestrate app are related to the completion status of an inquiry phase, and the following results are obtained: An average prior probability of 0.6 indicates that these operation logs predict the completion of the inquiry phase in m-Orchestrate, at 60%.

Figure 54 displays the outcomes of pyBKT analysis on student problem-solving sequences during the WeEngage phase. The pyBKT models determine students' completion results from database records to represent their mastery of a skill in the inquiry phase. The image shows the predictability of the operation logs at each checkpoint and the observed correctness of their answers. The image depicts the average predicted probability and the average observed correctness across all students. The results also suggest that two types of logs illustrate higher predictability concerning the completion status of this inquiry group in the WeEngage phase:

(1) creating and editing tables and blocks in the K and W columns in KWL tables (from 0.7–1) and (2) creating and editing a student note/a block of student notes (from 0.3–1).

Figure 54

Log Items' Ability to Predict the Completion of the WeEngage Phase



Actions below show higher predictability on the completion status of WeEngage phase

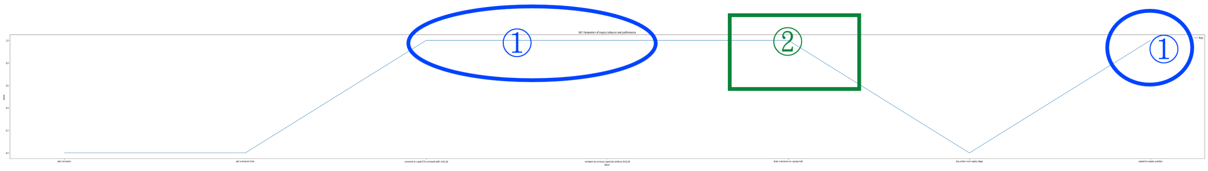
① creating and editing a **KWL table** and **blocks in K and W columns** in a KWL tables **(WeReflect)**

② creating and editing a **student note** / a **block** of a student note

Log Items' Ability to Predict the Completion of the WeCollect Phase. Figure 55 suggests that certain actions exhibit high predictability of the completion status of the WeCollect phase, in which students are empowered to engage in a range of activities. Students possess the capacity to include, observe, and revise their inquiry tasks, as well as opt for the specific data they wish to gather. Specifically, two types of logs demonstrate higher predictability: (1) raising and commenting on inquiry questions with a predictability of one and (2) creating and editing a student note with a consistent predictability score of 1.

Figure 55

Log Items' Ability to Predict the Completion of the WeCollect Phase



Actions below show higher predictability on the completion status of WeCollect phase

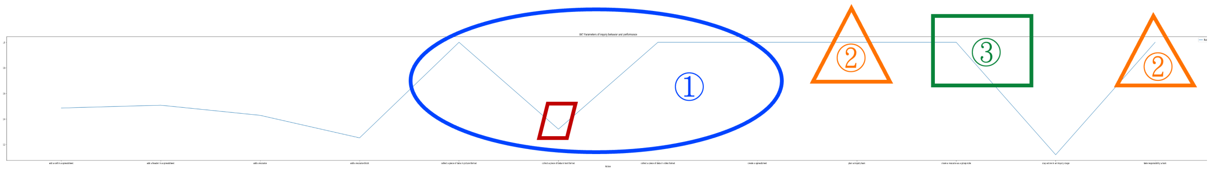
① raising and commenting on **inquiry questions** (WeEngage)

② creating / editing a **student note**

Log Items' Ability to Predict the Completion of the WeAnalyse Phase. Figure 56 suggests that certain actions exhibit high predictability concerning the completion status of the WeAnalyse phase, which provides an opportunity for group members to delve deeper into the collected data, enhancing their understanding and enabling them to draw well-informed conclusions from their discoveries. The results also reveal the higher predictability of the completion status: (1) collecting data in a picture, video, and spreadsheet (but no text) format (from 0.4 to 1), (2) planning a task and taking responsibility for it, with a predictability of 1, and (3) creating and editing student notes, with a consistent predictability score of 1.

Figure 56

Log Items' Ability to Predict the Completion of the WeAnalyse Phase



Actions below show higher predictability on the completion status of WeAnalyse phase

① **collecting data** in **picture/video/spreadsheet** (but low in **text**) format (**WeCollect**)

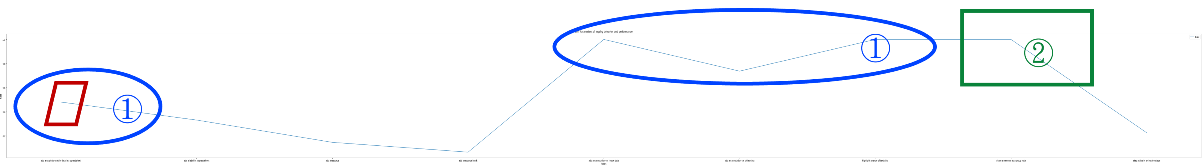
② **planning a task** and **taking responsibility** on a task (**WeCollect**)

③ creating and editing student notes

Log Items' Ability to Predict the Completion of the WeExplain Phase. The image in Figure 57 suggests that certain actions exhibit high predictability of the completion status of the WeExplain phase, which facilitates the presentation and sharing of inquiry processes by groups, allowing them to communicate their findings and results effectively. The results also reveal higher predictability of the completion status: (1) analyzing data in a text, image, and video (but not much in spreadsheets; from 0.8 to 1), and (2) creating and editing a student note, with the predictability of 1.

Figure 57

Log Items' Ability to Predict the Completion of the WeExplain Phase



Actions below show higher predictability on the completion status of WeExplain phase

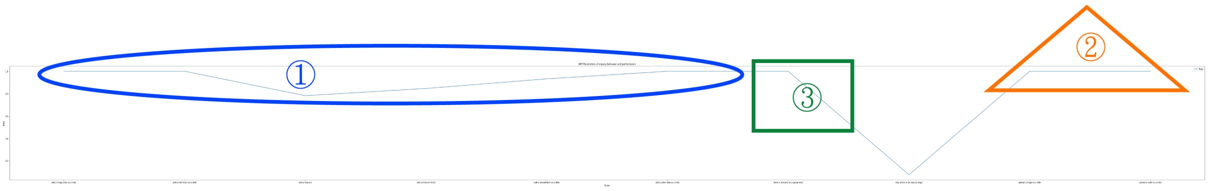
① **analyzing data** in **text/image/video** (but low in **spreadsheet**) format (**WeAnalyse**)

② creating and editing a **student note**

Log Items' Ability to Predict the Completion of the WeReflect Phase. Figure 58 suggests that certain actions exhibit good prediction of the completion status of the WeReflect phase, which supports users in reflecting on their learning journey by utilizing multimedia tools to revisit previous knowledge, pose inquiries for further exploration, and discuss obstacles encountered during the inquiry process. The results also show the good prediction of the completion status: (1) adding a student note, collected data, or analyzed data as a slide (from 0.8 to 1), (2) uploading an image or a video as a slide, with a predictability of 1; and (3) creating and editing a student note (from 0.5 to 1).

Figure 58

Log Items' Ability to Predict the Completion of a WeReflect Phase



Actions below show higher predictability on the completion status of WeReflect phase
① **adding a student note / collected data / analyzed data as a slide (WeExplain)**
② **uploading an image / a video as a slide (WeExplain)**
③ creating and editing a **student note**

In summary, these affordances of the LA tool empowered teachers to tailor their instructional interventions, provided targeted support, and designed appropriate scaffolding strategies to guide students' inquiry process effectively. By relying on evidence-based insights, teachers could make informed decisions, ensuring that their instructional practices aligned with students' needs, and optimize learning outcomes within the CSI context.

__4.4.3 Design Principles of Learning Analytics-Enhanced Teacher Orchestration Tools__

The LA tool was designed and developed by this study to align with the inquiry-based learning model with social constructivist theories (Vygotsky, 1978) and orchestration principles in terms of awareness, continuity, and flexibility in particular (Dillenbourg et al., 2011). Teachers should be aware of the inquiry status (e.g., off-task, progression) among groups' multiple learning trajectories (Gašević, Dawson & Pardo, 2016) among the five inquiry phases "WeEngage, WeExplore, WeAnalyse, WeExplain, and WeReflect." Awareness of students' inquiry status in orchestration CSI aimed at understanding students' inquiry status in real time. Continuity indicated in-time interventions to keep the smooth flow of students' inquiry on the right track (and avoid off-task activities): Redirecting students' CSI learning in a productive direction to maintain continuity (Slotta et al., 2013). Flexibility customized interventions for specific needs: Flexibly conducting interventions by determining the real-time needs of students at different social levels (Abrams et al., 2008). The following list summarizes the design principles of the LA tool for teacher orchestration.

1. The LA tool should follow theory-led co-design principles to align with the pedagogical goals and needs of teachers and students.
2. The design of the LA tool to support teacher orchestration in different phases and social levels of CSI should provide affordances for awareness, continuity, and flexibility.
3. Awareness affordances should include features such as nesting students' inquiry activities, tracking the status of inquiry-based learning activities, showing the "Raise Hand" icon, presenting pre-planned schedules, providing a zoom slider and group filter, and integrating EDM strategies (i.e. bupaR) to go into insights of students' CSI processes.

4. Continuity affordances should include features such as revealing students' real time status of CSI by process analysis (i.e. the bupaR features in this study), releasing resources, and giving feedback at both the class and group levels as well as providing relevant interventions with continuity.
5. Flexibility affordances should include features such as enabling teachers to provide interventions both in advance and on the fly, supplying related resources and feedback to students on different social levels, regarding the group difference of students' behaviors contributing to the achievement of CSI projects (i.e. the pyBKT features to indicate the students' behaviors relating to the completion of inquiry phases in this study) and displaying previous interventions conducted through the LA tool for in-time adjustments.

The principles that confirm the past studies and findings are those that align with the existing design principles in the literature, such as providing affordances for awareness, continuity, and flexibility in teacher orchestration of inquiry-based learning. These principles are informed by social constructivist theories and orchestration principles. The new principles derived from the current DBR study are those that specify the features of the LA tool that support teacher orchestration in different phases and social levels of CSI.

The principles that are worth of further investigation are those that have not been empirically tested or validated in different settings or with different populations, such as how the LA tool affects students' learning outcomes, motivation, and engagement in CSI; how teachers perceive and use the LA tool in different inquiry phases and social levels; how the LA tool can be integrated with other digital tools and resources for CSI; and how the LA tool can be adapted or improved to meet the diverse needs and preferences of teachers and students.

Chapter 5: Discussions

The study analyzed data from each cycle, and the discussions centered around four main topics: (1) the theory-led Learning Analytics (LA) Tool design and development for teacher orchestration of student Collaborative Science Inquiry (CSI) in a Mobile Learning Environment (MLE), (2) the technical design and development of the LA tool with the three affordances for teacher orchestration of CSI in an MLE, (3) approaches of integrating the theory-led LA tool into teacher orchestration of student CSI in an MLE, and (4) theoretical, practical, and technical contributions of the study.

5.1 Theory-Led Learning Analytics Tool Design and Development for Teacher Orchestration of Student Collaborative Science Inquiry in a Mobile Learning Environment

Learning Analytics (LA) tools are technologies and methods that collect, analyze, and visualize data about learners and their interactions with learning environments (Siemens, 2010). These tools provide feedback, guidance, and support for both learners and teachers, facilitating the assessment and evaluation of learning processes and outcomes. This section discusses how LA tools can bridge the gap between teacher orchestration and students' Collaborative Science Inquiry (CSI) learning in a Mobile Learning Environment (MLE).

CSI learning involves engaging students in authentic scientific practices such as questioning, designing experiments, collecting and analyzing data, and communicating findings (Bell et al., 2010). It promotes students' conceptual understanding, epistemic awareness, and scientific reasoning skills (Chu et al., 2012). However, CSI learning presents challenges for both students and teachers. Students may face difficulties with the complexity and uncertainty of scientific problems, coordinating and regulating collaborative activities, and reflecting on and evaluating their contributions and those of their peers (Wise & Schwarz, 2017). Teachers may find it challenging to monitor and support multiple groups of students working on different aspects of an inquiry and provide timely and appropriate feedback and scaffolding (Erickson, 1991).

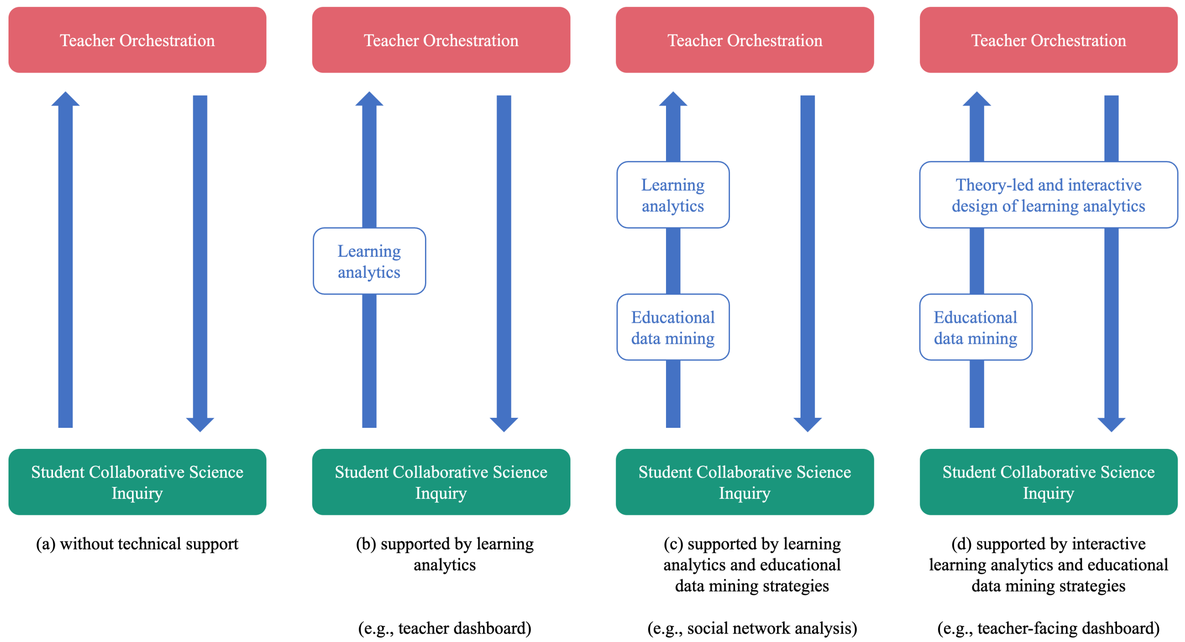
An MLE refers to learning environments that leverage the capabilities of mobile devices such as smartphones, tablets, and laptops to enable flexible, personalized, and situated learning experiences (Quan et al., 2022; Sharples et al., 2016). An MLE can support CSI learning by providing access to multimedia resources, interactive simulations, data collection tools, and communication channels (Jong & Tsai, 2016). It also facilitates collaboration among students, whether they are co-located or distributed across locations (Chiang et al., 2014). However, an MLE introduces new challenges for teacher orchestration and student regulation. Teachers may have limited visibility and control over students' activities and progress in an MLE, while students may face distractions and interruptions from their surroundings or other applications.

LA tools can bridge the gap between teacher orchestration and student CSI learning in an MLE by providing meaningful information about the inquiry process and outcomes to both teachers and students. For teachers, LA tools can track students' actions, interactions, and achievements in an MLE, identifying patterns, trends, and outliers that may require intervention or present opportunities (Verbert et al., 2014). Visualizations of students' navigation paths, resource usage, collaboration patterns, knowledge-building trajectories, and inquiry outcomes in an MLE can inform teachers' decisions regarding the orchestration of the inquiry process, such as grouping students, assigning tasks, providing hints or prompts, or initiating whole-class discussions (Saleh et al., 2022; Yang et al., 2020).

Figure 59 presented existing technology-enhanced solutions to support teacher orchestration of the student CSI process. Traditionally, the teacher orchestration relied on direct observation in person, which might miss some information from different groups as the teacher could only focus on one group at the same time. Also, because the process of CSI was complex, it might cause a loss of necessary interventions among various phases and activities to keep students learning effectively (Berland et al., 2015). Some scholars adopted LA technologies that could provide visualized information on students' CSI processes (Han & Ellis, 2021; Nistor et al., 2018; Prieto et al., 2019). Some scholars also adopted EDM approaches to dig out more potential information from data and provide it in LA dashboards or visualization (Baker et al., 2016). There was still a gap between the information from LA tools and EDM results to pedagogical actions (Er et al., 2021; McKenney & Mor, 2015; Saggi & Jain, 2018). With guidance from the theoretical perspectives and interactive features, teachers could directly conduct just-in-time and "working-well" orchestration practices based on the status and needs of students' CSI from LA and EDM results (Aldowah et al., 2019; Du et al., 2021; Koedinger et al., 2015).

Figure 59

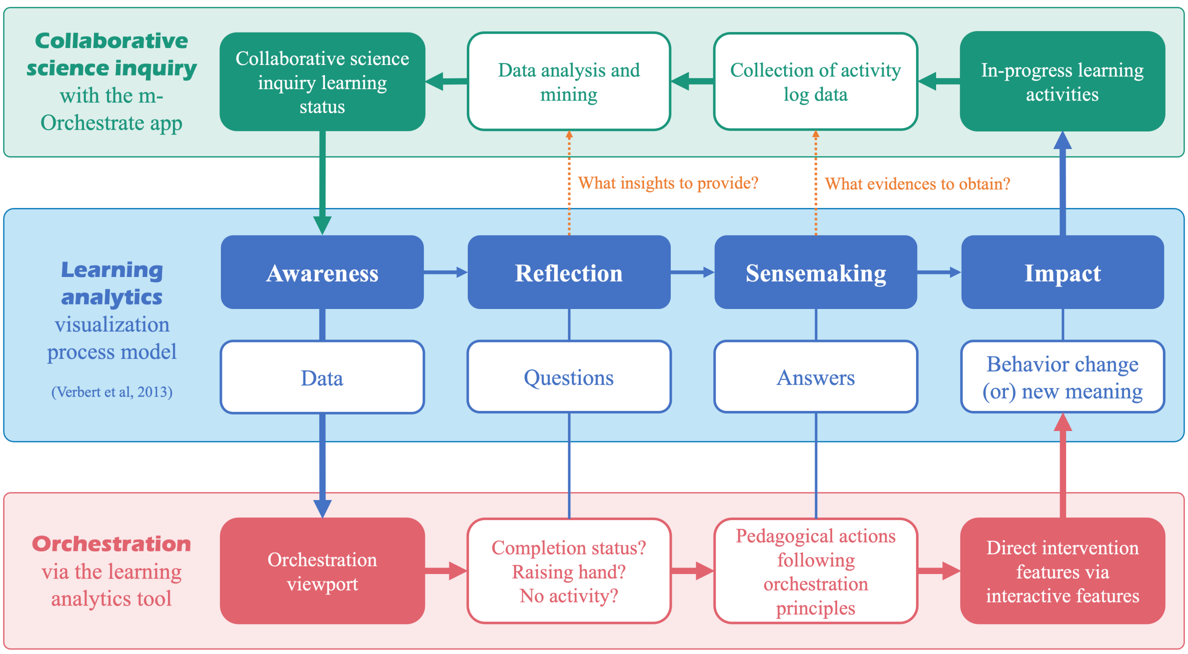
Different Solutions of LA-Enhanced Teacher Orchestration of Student Collaborative Science Inquiry in a Mobile Learning Environment



This study worked out a process model of how the newly developed theory-driven LA tool helped enhance teacher orchestration of CSI in an MLE. The process model (see Figure 60) was summarized based on the DBR involving design, development, implementation, and refinement of the theory-led LA tool. This model explains the role of LA as a technology approach to enhancing teacher orchestration of student CSI learning in an MLE. Various log data can be generated during the CSI learning process in an MLE. For example, in this study, the log data on the m-Orchestrate app contains student real time inquiry status. These data could reflect students' learning status of collaboration and inquiry. If the data can be analyzed, and visualized, it can provide actionable information for just-in-time orchestration practice (Verbert et al., 2013). However, even though the visualization of data can inform some meaningful pedagogical actions, the teacher may still feel confused about what is happening and what should do. An educational theory takes into account the nature of a teaching and learning context and interprets the indicators in a meaningful and understandable way for making educational decision making (Cao & Song, 2019). In this study, the design and development of the LA tool were aligned with the orchestration principles, which indicated how a pedagogical intervention worked well (Dillenbourg, 2013). The DBR adopted a series of LA approaches as affordances, including (1) interactive features for just-in-time intervention, (2) bupaR analysis to understand students' CSI process, and (3) pyBKT to recognize students' behaviors with a higher ability to predict the completion of CSI phases from previous projects. These affordances could directly guide the teacher to know significant concerns from data and to shape relevant actions as orchestration of CSI in an MLE in terms of awareness, continuity, and flexibility principles (Dillenbourg & Jermann, 2010).

Figure 60

A Process Model of LA-Enhanced Teacher Orchestration of Student CSI in an MLE



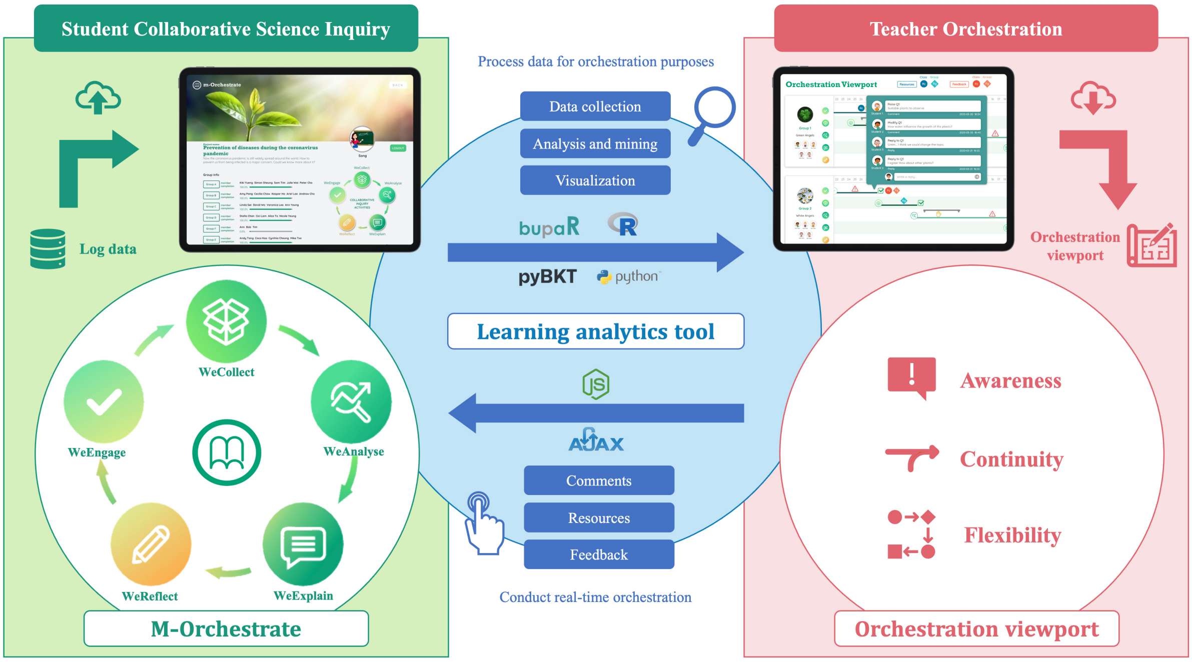
5.2 Technical Design and Development of the Learning Analytics Tool with the Three Affordances for Teacher Orchestration of Student Collaborative Science Inquiry in a Mobile Learning Environment

The LA tool developed to support teachers' orchestration in CSI contexts has significant implications for learning and teaching. The design and development of the tool were guided by theory-led (Kelly et al., 2015) and co-design approaches (Prieto et al., 2019) incorporating the CSI learning model into an MLE and the concept of orchestration.

Figure 61 shows how the refined theory-led LA tool works on the m-Orchestrate app. The LA tool's layout design follows (1) the CSI learning model grounded in social constructivist theories (Vygotsky, 1978) and (2) three key principles of teacher orchestration of CSI. The LA tool gathers data from the m-Orchestrate app and then cleans, organizes, and visualizes them in a theory-led design of the orchestration viewport. The information is provided on the viewport for teacher orchestration purposes, especially for awareness, continuity, and flexibility (Dillenbourg, 2013, 2015; Rodríguez-Triana et al., 2015; Slotta et al., 2013; Tissenbaum & Slotta, 2019b). Teachers can think of interventions based on these orchestration principles according to students' inquiry status. Finally, teachers can use interactive functions in the viewport to comment on specific contents in specific phases and positions on the m-Orchestrate app, provide resources and feedback, and notify students to support their real-time needs. After three cycles of refinements, the LA tool was equipped with advanced EDM approaches (bupaR and pyBKT) to get more insights into students' CSI learning status and patterns, which also match the orchestration needs raised by teachers during their practices. Interfaces of the orchestration viewport were also redesigned to be more straightforward for teachers' just-in-time interventions.

Figure 61

System Framework of the Theory-Led LA Tool



The theory-led LA tool's affordances for teacher orchestration of CSI in an MLE are (1) the interactive features for supporting students' CSI learning in five phases on the m-Orchestrate app, (2) visualizing students' CSI learning process in detail using bupaR in an MLE, and (3) analyzing abilities of students' behaviors to predict completion of an inquiry phase by using pyBKT. The LA tool facilitates teachers in managing multiple groups of students working on complex and open-ended scientific problems (Rodríguez-Triana et al., 2015) in an MLE while supporting students in regulating and improving their collaborative inquiry skills and strategies (Amarasinghe et al., 2022) in an MLE. The LA tool's affordances enhance teacher awareness, continuity, and flexibility (Dillenbourg & Jermann, 2010) in orchestrating CSI activities.

These affordances are facilitated by features such as visualizing students' inquiry activities, monitoring the progress of inquiry-based learning activities, delivering resources and feedback at different social levels, and enabling proactive and reactive teacher interventions (Manathunga et al., 2015). The orchestration viewport within the LA tool allows teachers to make informed decisions and interventions by utilizing information from the LA tool (Suárez et al., 2018). The viewport also provides control over certain aspects of the LA tool, such as adjusting difficulty levels or providing students with feedback. The design of the viewport aligns with orchestration principles, being minimalist, practical, and flexible.

5.2.1 Interactive Features for Teacher Orchestration

The interactive features of the developed and refined LA tool provide affordances for awareness, continuity, and flexibility of teaching orchestration of student CSI in an MLE throughout this study. The LA tool (1) adopts teacher orchestration needs (Berland et al., 2015; Nasir et al., 2021; Zhu & Wang, 2020), (2) obtains more insights into CSI in an MLE (Linn et al., 2015; Marchal–Crespo et al., 2014), and (3) provides direct and interactive ways of fostering further orchestration practices (Cao & Song, 2020). Inspired by the orchestration graph (Dillenbourg, 2015), behavior information at diverse social levels is presented in the design of the viewport in Figure 42.

The LA tool provides teachers with a holistic view of students' inquiry status by listing all groups of a class in the same view. Teachers can monitor students' inquiry activities and provide feedback individually. The timeline can be clicked to show specific activities in a pop-up bubble (See Figure 43). Teachers can zoom in or out of the timeline to focus on specific learning activities in various inquiry phases. By selecting one or more groups, teachers can obtain a clear view of students' learning trajectories.

The orchestration viewport provides features for just-in-time interventions for teacher orchestration in the five inquiry phases of CSI at the group and class levels. Teachers can release "Resources" (see Figure 44) and give "Feedback" (Figure 45) by clicking on the two navigation bars in the specific inquiry phase and activity. Based on the learning trajectories of diverse groups, relevant interventions with continuity can be released directly on the dashboard to maintain a smooth flow for each group's learning activities. Teachers can provide interventions both in advance and on the fly with flexibility according to pedagogical needs.

5.2.2 BupaR Analysis of Students' Collaborative Science Inquiry in a Mobile Learning Environment

bupaR adopted in this study is an open-source, integrated R package for handling and analyzing business process data (Janssenswillen et al., 2019). Using bupaR to perform a regression analysis is able to determine which factors are most predictive of student performance. This can help with the identification of the relative importance of each factor and make recommendations for improving a course based on analyses (Ong et al., 2021). It can also be used to create visualizations of the results of analyses, such as scatter plots, histograms, and box plots (Schwendimann et al., 2017). These visualizations can facilitate the understanding of the relationships between variables and communicate the results of the analyses to others.

5.2.3 PyBKT Analysis of Students' CSI Learning

This study applied pyBKT (Anirudhan et al., 2021) to analyze students' inquiry behaviors and performance in the CSI learning process. Based on students' behaviors from the same inquiry group in the completed project, the pyBKT analysis indicated the predictabilities of the group of students' behaviors on the completion of five inquiry phases, namely, WeEngage, WeCollect, WeAnalyse, WeExplain, and WeReflect. The pyBKT used operation logs from the m-Orchestrate app to predict the completion status of each inquiry phase and to identify the types of logs that have higher predictability. The results show that general activity data (such as visiting or clicking on events in inquiry phases) were less useful for predicting group performance while logging data that aligned with inquiry theories (such as raising questions, collecting data, analyzing data, and creating notes) were more valuable (G. W. Chen, 2020). The results of pyBKT features also revealed the differences in predictability among different inquiry phases and students' behaviors (Berland et al., 2015).

5.3 Approaches of Integrating the Theory-Led Learning Analytics Tool into Teacher Orchestration of Student Collaborative Science Inquiry in a Mobile Learning Environment

This section discusses the approaches to integrating the theory-led Learning Analytics (LA) tool into teacher orchestration of student Collaborative Science Inquiry (CSI) in a Mobile Learning Environment (MLE). It discusses how the tool impacted teacher orchestration and student learning performance in the context of CSI. The benefits and implications of the LA tool for teacher orchestration were recognized, such as enhanced monitoring, feedback, and adaptation capabilities. Then, the section discusses how the LA-enhanced teacher orchestration impact student learning performance (e.g., increased motivation and understanding of CSI concepts).

5.3.1 Theory-Led Learning Analytics Tool's Impact on the Teacher Orchestration

This study explored the impact of the theory-led (Kelly et al., 2015) LA tool on teacher orchestration in the CSI context. The integration of theory-led LA tools provided teachers with enhanced capabilities to orchestrate their instructional activities effectively. The theory-led LA tool integrated into the m-Orchestrate app provided teachers with a range of benefits that positively influenced their orchestration of CSI.

The theory-led LA tool included interactive features to support teacher orchestration of student CSI in an MLE. These features allowed teachers to (1) monitor students' progress and receive notifications of important events, (2) facilitate students' transition between formal and informal settings and provide relevant interventions, and (3) adapt and customize the inquiry phases and resources according to students' needs and interests. Advanced EDM strategies were also adopted by the LA tool. Business Process Analytics in R (bupaR) allowed teachers to explore students' behaviors and patterns in greater depth (Janssenswillen et al., 2019). The insights from bupaR could be utilized to examine the details of students' learning processes and provide relevant resources and feedback. The LA tool also incorporated Python implementation of the Bayesian Knowledge Tracing (pyBKT) (Anirudhan et al., 2021) to analyze the log data of students' learning activities and provide feedback and guidance. It generated an interactive list that presented students' behaviors with highly predictable progress and the completion of inquiry phases based on previous projects. PyBKT also aided teachers in identifying students' strengths and weaknesses and helped in planning future interventions.

The LA tool enabled teachers to gain a deeper understanding of students' learning processes and progress. By collecting and analyzing data on students' performance, and behavior, teachers could identify patterns, trends, and areas of improvement. The evidence from the data augmented teachers' awareness of individual student needs and helped them make informed decisions regarding instructional strategies, interventions, and scaffolding (Verbert et al., 2013). The theory-led LA tool also supported teachers in providing timely and targeted feedback to students (Holstein et al., 2019). By leveraging the analytics provided by the tool, teachers could identify specific areas where students required additional support or clarification (Gašević, Dawson, Rogers & Gasevic, 2016). It allowed teachers to address misconceptions promptly and guide students toward achieving mastery of concepts and skills during CSI (Manathunga et al., 2015).

Furthermore, the theory-led LA tool facilitated the identification of students at risk of falling behind or requiring extra assistance (Hung et al., 2017). By analyzing data on student performance, teachers could proactively intervene and provide targeted support to help struggling students (Slotta et al., 2013). This early identification of students in need allowed timely interventions and prevented the widening of achievement gaps. The tool empowered teachers to implement differentiated instructional strategies, address individual student challenges, and promote better learning outcomes in CSI (Tissenbaum & Slotta, 2019b).

The impact of the theory-led LA tool extended beyond individual students to the entire CSI processes in an MLE (Amarasinghe et al., 2022; McKenney & Mor, 2015; Worsley & Blikstein, 2014). Teachers could use the tool to monitor class-wide progress, identify common misconceptions, and adjust their instructional approaches accordingly (Rodríguez-Triana et al., 2015). The aggregated data provided by the tool allowed teachers to assess the effectiveness of their pedagogical practices and make data-informed decisions to optimize instructional delivery(Han & Ellis, 2021). This evidence-based approach enhanced the overall quality of instruction and fostered continuous improvement in CSI teaching (Zheng et al., 2021).

Moreover, the theory-led LA tool promoted reflective practice among teachers. By providing visualizations, reports, and analytics of student learning, the tool encouraged teachers to reflect on their instructional practices and refine their teaching strategies (Suárez et al., 2018). Teachers could evaluate the impact of their pedagogical decisions, identify strengths and areas for improvement, and engage in ongoing professional development (Jones et al., 2013). The tool's feedback loop enabled teachers to iterate and adapt their instructional approaches based on real-time data, leading to the continuous enhancement of their orchestration skills in CSI (Munneke et al., 2007).

5.3.2 Student Learning Performance under Learning Analytics-Enhanced Teacher Orchestration

Teacher orchestration supported by the theory-led LA tool also augmented student performance. Students showed increased motivation and understanding of CSI concepts. There was a marked amelioration of domain test scores, which was attributed to personalized learning experiences, ongoing assessment practices, student activity and self-monitoring, and collaborative learning opportunities (Chatti et al., 2021). Both qualitative and quantitative data were collected and analyzed. The impact of LA-enhanced teacher orchestration on student learning performance was reflected below.

The LA tool provided real-time data monitoring and visualization, enabling teachers to gain immediate insights into students' progress, engagement, and interactions during CSI. These affordances equipped teachers with the ability to identify patterns, anticipate challenges, and make timely instructional adjustments to optimize students' learning outcomes (Nistor et al., 2018). By visualizing data through intuitive dashboards and visual representations, teachers could effectively track student performance and make informed decisions to scaffold and support their students' inquiry process (Er et al., 2021).

The LA tool facilitated teachers' adaptive feedback and guidance, personalized to each student's unique needs and progress within the CSI activities. Leveraging the power of LA, the tool helped analyze student data to offer tailored feedback, problem-solving strategies, and resources (Ong et al., 2021). This affordance promoted self-regulation and empowered students to take ownership of their learning process while receiving personalized support from the teacher (McKenney & Mor, 2015). By providing individualized feedback and guidance, teachers could foster critical thinking skills, enhance problem-solving abilities, and promote deeper engagement in the CSI process.

The LA tool supported data-driven decision making for teacher orchestration. By analyzing the data collected during CSI activities, teachers could identify individual and collective learning gaps, misconceptions, or challenges (Han & Ellis, 2021). The LA tool also incorporated advanced LA strategies, specifically bupaR and pyBKT, to provide deeper insights into students' CSI learning status and styles at the group level.

The feedback from teacher interviews revealed that teacher orchestration supported by the theory-led LA tool improved students' learning performance in CSI (Schwendimann et al., 2017). Using the LA tool, teachers monitored students' progress, provided personalized feedback, and designed targeted interventions. This resulted in greater student participation, more active involvement in learning activities, and a better conceptual understanding (Romero & Ventura, 2020). Via the LA tool, individual variations were observed in student performance. Factors such as prior knowledge, learning styles, and the extent of student engagement with the LA tool influenced these variations. Teachers appreciated the personalized support and felt more confident in their pedagogical practices to help students succeed in CSI.

Building on these qualitative insights, the quantitative analysis focused on the impact of teacher orchestration on students' domain test performance. The data analysis indicated a significant improvement in students' domain test scores following the implementation of teacher orchestration supported by the LA tool (Pelánek, 2020). The LA tool personalized learning experiences by enabling teachers to identify students' specific needs and tailor instruction accordingly. This targeted approach helped address individual learning gaps and resulted in heightened test performance.

5.4 Contributions of the Study

This section presents the contributions of this Design-Based Research (DBR) to the field of Learning Analytics (LA)-enhanced teacher orchestration of Collaborative Science Inquiry (CSI) in a Mobile Learning Environment (MLE). The contributions lie in three aspects: theoretical, technical, and practical.

5.4.1 Theoretical Contributions

This study adopting DBR made three primary theoretical contributions to technology-enhanced teacher orchestration of CSI in an MLE with the LA tool.

1. Adopting a theory-led approach (Kelly et al., 2015) to designing and redesigning an LA tool for orchestration,
2. Identifying a process model of the LA-enhanced orchestration of students' CSI in the MLE process, and
3. Developing the design principles of an LA tool to support the teacher orchestration of students' CSI in an MLE

This study has developed a process model and design principles of LA-enhanced orchestration of CSI in an MLE. The study also adopted a theory-led approach to designing and redesigning an LA tool for orchestration. This approach was based on the idea that theories can help guide the design process and ensure that the tool is effective in achieving its intended goals. The study identified a process model of the LA-enhanced orchestration of students' CSI in the MLE process. The model summarizes the process and mechanism that how a LA tool can assist and enhance teacher orchestration of student CSI learning activities. The study delivered the design principles of an LA tool to support the teacher orchestration of students' CSI in an MLE. These design principles of an LA-enhanced orchestration tool were based on the findings from the previous two contributions and were designed to help teachers use LA tools more effectively in their teaching practice.

5.4.2 Technical Contributions

This study also made three main technical contributions to the understanding of teacher orchestration of CSI in an MLE with the LA tool.

1. Developing interactive features to the LA tool to support students' CSI learning in five phases on the m-Orchestrate app,
2. Using Business Process Analytics in R (bupaR) to analyze students' CSI behaviors and outcomes in an MLE and analyze teachers' orchestration practices and challenges, and
3. Using Python implementation of the Bayesian Knowledge Tracing (pyBKT) to analyze students' CSI learning processes from the same group in previous projects and predict the highly-related behaviors to the completion of each inquiry phase.

The m-Orchestrate app developed in Phase I of the DBR is a learning system that aims at supporting teacher orchestration and student collaborative science inquiry in an MLE. The study also developed an interactive and theory-led LA tool in Phase II, which could involve the practice of teacher orchestration of CSI learning on the m-Orchestrate app. The interactive features of the LA tool with specific pedagogical orientations can address teacher orchestration needs while conducting CSI. The LA tool also added the bupaR and pyBKT in Cycle 2 and Cycle 3 of Phase III to analyze students' CSI behaviors, processes, patterns, and differences among different inquiry groups in an MLE to provide more insights for teacher orchestration.

5.4.3 Practical Contributions

This DBR made three primary practical contributions to supporting and understanding teacher orchestration of CSI in an MLE with the LA tool.

1. Redesigning and developing the m-Orchestrate app from the m-Orchestrate web platform to address students' CSI learning needs more specifically,
2. Developing the theory-led LA tool in collaboration with participating teachers based on their pedagogical needs in practice, and
3. Enriching empirical studies on using LA to support the orchestration of students' CSI in an MLE.

This study developed both the m-Orchestrate app and the LA tool based on social constructivist theories (Vygotsky, 1978) and orchestration principles (Dillenbourg & Jermann, 2010) to provide practical support to the needs of both students CSI learning and teacher orchestration. The DBR included implementations in three cycles of Phase III to understand and evaluate the impact of the LA tool on teacher orchestration and students' CSI learning performance. The pedagogical practices with the LA tool can be scaled up in more of Hong Kong's even Greater Bay Area (GBA)'s primary schools for effective teacher orchestration of CSI in an MLA.

The Conclusion chapter in Chapter 6 summarizes the DBR and its major findings, which explored the potential of LA technology to support teacher orchestration practice in CSI learning inside and outside the classroom.

Chapter 6: Conclusions

This study explored the potential of LA technology to support teacher orchestration practice in CSI learning inside and outside the classroom. It proposed the design of a theory-led LA tool that could help teachers monitor students' CSI process and make "just-in-time" pedagogical decisions in an MLE. The study aimed to address the challenges and gaps in the current literature and practice of CSI, such as the complexity of teacher orchestration, the lack of theory-based LA tools, and the need for cross-contextual support.

The needs and challenges of the teacher orchestration of CSI learning in an MLE and the potential of LA to support it have been addressed in the review section. It has discussed existing LA tools that have been applied to support teacher orchestration. It has also highlighted the key issues of LA tools during implementation, such as a lack of teacher training and support, limited integration with existing practices, data interpretation and actionability, and capturing complex aspects of the learning process. Based on the literature review, the research gaps and objectives of this study were identified, which aimed to develop and implement an LA tool based on CSI theory, primary orchestration principles, and DBR methods in Hong Kong's primary schools.

The study adopting DBR aimed to (1) identify the needs of teachers' orchestration of CSI in an MLE, (2) design and develop a theory-led LA tool, (3) implement and refine the LA tool in practice, and (4) provide the LA tool as an artifact with design principles. Through the 3-cycle implementation, the LA tool, designed, and aligned with theory, provided teachers with valuable opportunities to orchestrate CSI activities effectively, resulting in heightened student engagement, comprehension, and performance. Cycle 1 identified the challenges and needs of the teachers in orchestrating CSI and the potential of LA to address them. Cycle 2 developed and evaluated an interactive dashboard with LA that provided teachers with real-time data and analytics on students' inquiry progress, engagement, performance, and collaboration. Cycle 3 added a pyBKT feature to the LA tool that gave teachers more detailed and dynamic information on students' inquiry styles and learning trajectories.

The study investigated the affordances and impact of a theory-led LA tool for teacher orchestration in Computer Science Inquiry CSI. The findings are as follows:

For RQ1, the theory-led LA tool integrates interactive, bupaR, and pyBKT features to provide several affordances for teacher orchestration in CSI. These affordances include enhancing teachers' awareness of students' inquiry behaviors and performance, supporting teachers' continuity of instruction, and increasing teachers' flexibility of instruction.

For RQ2, the theory-led LA tool has a positive impact on teacher orchestration in CSI. It improves the efficiency and effectiveness of teacher orchestration, facilitates the quality and quantity of teacher-student interactions, and promotes the alignment and coherence of teacher orchestration with the inquiry learning goals and theories. Additionally, the LA tool helps reduce teachers' cognitive overload on interpreting data.

For RQ3, teacher orchestration supported by the theory-led LA tool has a positive impact on student learning performance in CSI. It enhances students' domain knowledge acquisition, fosters students' inquiry skills development, and motivates students' inquiry interest and engagement.

In summary, the findings from the three iterative cycles in Phase III of the DBR showed that the LA tool with the interactive dashboard and the pyBKT feature was generally useful and effective for supporting teacher orchestration. The findings showed that the LA tool was useful and effective for enhancing teacher orchestration practices and students' domain knowledge acquisition in CSI. The DBR also advanced our knowledge and understanding of how the theory-led LA tools could support teacher orchestration and optimize student learning outcomes in CSI in an MLE. These findings contribute to our understanding of the potential benefits of theory-led LA tools for teacher orchestration in CSI. However, it is important to note that these findings are based on the materials provided and may vary depending on the specific context and implementation of the theory-led LA tool in CSI.

Chapter 7: Limitations

This study contributes to the field of Learning Analytics (LA) regarding LA tool design, development, and implementation for teacher orchestration of students' Collaborative Science Inquiry (CSI) learning in a Mobile Learning Environment (MLE). However, this study also has limitations that should be acknowledged and addressed in future research. These limitations are related to the scope, design, implementation, and evaluation of the LA tool and the m-Orchestrate app, which are presented below.

First, this study focused on primary school students in Hong Kong involved in scientific inquiry activities using the m-Orchestrate app in the domain of General Studies. Therefore, the findings and implications of this study might not be generalizable to other age groups, regions, contexts, or learning domains.

Second, this study focused on a limited number of LA indicators and dashboards that were relevant to the specific pedagogical goals and design principles of the m-Orchestrate app. Therefore, the LA tool and the m-Orchestrate app might not capture or provide all the necessary information and feedback that teachers and students need for effective orchestration and learning in an MLE.

Third, this study adopted Design-Based Research (DBR) that involved teachers and the researcher as co-designers of the LA tool and the m-Orchestrate app. Although this approach has many advantages, such as enhancing the usability, relevance, and acceptance of the LA tool and the m-Orchestrate app, it also has drawbacks, such as introducing biases, preferences, and expectations that may not reflect the needs or perspectives of other potential users.

Fourth, this study faced challenges in accessing some schools and partners involved in or interested in integrating LA into CSI teaching and learning in an MLE. For example, some schools were reluctant or unable to participate in the study for various reasons, such as a lack of resources, time constraints, curriculum alignment issues, or ethical concerns. Moreover, some teachers and students could not use or access the LA tool or the m-Orchestrate app due to technical problems, such as device compatibility issues, software bugs, or network failures.

Fifth, this study conducted only three rounds of two-week interventions during implementations with two teachers and their two classes of students who used the LA tool and the m-Orchestrate app for teacher orchestration of CSI and student learning for a relatively short time. Therefore, the results might not reflect the long-term effects or impacts of using the LA tool and the m-Orchestrate app on orchestration and learning outcomes in an MLE.

Chapter 8: Future Work

This study designed, developed, and implemented the Learning Analytics (LA) tool for supporting teacher orchestration of students' Collaborative Science Inquiry (CSI) learning in a Mobile Learning Environment (MLE). Future research could extend the scope of this study by applying the Learning Analytics (LA) tool and the m-Orchestrate app to different educational settings and domains, such as vocational training and higher education, and to other subject areas, such as mathematics and language arts.

Moreover, future research could explore the cross-cultural and cross-border aspects of LA and CSI learning by involving students and teachers from various countries and regions, such as the Greater Bay Area (GBA).

To expand the scope of this study, future research could develop and evaluate more LA indicators and dashboards that address other aspects of orchestration and learning in an MLE. These aspects include collaboration, motivation, engagement, metacognition, and self-regulation.

To overcome the limitation of stakeholder involvement in the design process of the LA tool and the m-Orchestrate app, future research could engage a larger and more diverse group of stakeholders. This group may include researchers, developers, policymakers, parents, and experts.

To address the limitation of collaboration with schools and partners in LA-supported teacher orchestration in CSI and student learning in an MLE, future research could establish more collaborations and partnerships. These collaborations should involve schools and partners that are willing to participate in LA-supported teacher orchestration.

To overcome the limitation of a small sample size in this study, future research could conduct more longitudinal studies with larger groups of teachers and students.

Besides the potential optimization based on the limitations, two more directions for future work can extend and improve this research which is presented as follows.

8.1 Scaling up the Implementation of the Learning Analytics Tool for Teacher Orchestration of Collaborative Science Inquiry

One possible direction for future work is to scale up the implementation of the LA tool for teacher orchestration of CSI in an MLE from Hong Kong to the GBA and to create generic application programming interfaces (APIs) that can be deployed and work on other platforms, such as Moodle. This would enhance the scalability and transferability of the LA tool, as well as increase its potential impact on teacher orchestration and students' learning outcomes.

The LA tool is a mobile learning solution that integrates mobile technology into the science curriculum, assessment, collaboration, and inquiry-based pedagogy grounded in social constructivist theories. Currently, the LA tool is designed and implemented for primary school students in Hong Kong. However, it would be valuable to extend its application to other regions and contexts, such as the GBA. By scaling up the implementation of the LA tool to the GBA, we could explore how the LA tool can support students' CSI learning in different cultural and educational settings (e.g., vocational training and higher education) and how it can foster cross-border collaboration and exchange among students and teachers.

8.2 Smart Orchestration

Future research will explore the technical solutions and principles of how Large Language Models (LLMs) can provide smart instructional intervention suggestions as “smart orchestration” of Collaborative Science Inquiry (CSI) in a Mobile Learning Environment (MLE) based on LA results. LLMs are neural network models trained on massive amounts of text data that can generate natural language texts for various tasks and domains (Kew & Tasir, 2022). LLMs (i.e., ChatGPT, Bing AI Chat, Google Meet Bard) have shown remarkable capabilities for generating fluent, coherent, and informative texts that can be used for various educational purposes, such as summarizing, answering questions, and generating feedback. Therefore, in the future, LA research can explore how LLMs can be leveraged to provide smart instruction or intervention suggestions for teachers based on LA results for just-in-time pedagogical refinement and decision-making.

Furthermore, more advanced technologies have the potential to support teacher orchestration needs in CSI in an MLE. For example, Qiuvr (Girard, 2023) is a tool that assists teachers in reviewing students’ artifacts efficiently and providing feedback or suggestions. It uses the OpenAI CLIP neural network to analyze and comprehend uploaded works in various formats, such as text, images, documents, slides, or reports. Future research can be explored regarding how to integrate cutting-edge technologies as an option for LA in CSI in an MLE.

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Appendix A

BupaR Source Code to Analyze Teacher Operation of the LA Tool

```r
# Set working folder
setwd("~/R-mo-teaching")

# Install libraries
install.packages('plyr')
install.packages('bupaverse')
install.packages('processanimateR')
install.packages('markdown')

# Load libraries
library(plyr)
library(bupaverse)
library(processanimateR)
library(markdown)

# Data import
data <- read.csv(
'mo_la_tool_log_data.csv', sep = ",", encoding = "UTF-8"
)

# Cycle 1 - The teacher from Experiment Group 1
c1_e1 <- data %>% filter(class_name == 'c1_e1')
```

```
# Creating eventlog
c1_e1_eventlog <- c1_e1 %>%
# Rename timestamp variables appropriately
dplyr::rename(start = created_at, complete = updated_at) %>%
# Convert time format
convert_timestamps(
columns = c("start", "complete"), format = ymd_hms
) %>%
activitylog(
case_id = "teacher_id",
activity_id = "teacher_action",
timestamps = c("start", "complete"),
resource_id = "teacher_name"
) %>%
to_eventlog()

# Cycle 2 - The teacher from Experiment Group 1
c2_e1 <- data %>% filter(class_name == 'c2_e1')
# Creating eventlog
c2_e1_eventlog <- c2_e1 %>%
# Rename timestamp variables appropriately
dplyr::rename(start = created_at, complete = updated_at) %>%
# Convert time format
convert_timestamps(
```

```
columns = c("start", "complete"), format = ymd_hms
) %>%
activitylog(
case_id = "teacher_id",
activity_id = "teacher_action",
timestamps = c("start", "complete"),
resource_id = "teacher_name"
) %>%
to_eventlog()

# Cycle 2 - The teacher from Experiment Group 2
c2_e2 <- data %>% filter(class_name == 'c2_e2')
# Creating eventlog
c2_e2_eventlog <- c2_e2 %>%
# Rename timestamp variables appropriately
dplyr::rename(start = created_at, complete = updated_at) %>%
# Convert time format
convert_timestamps(
columns = c("start", "complete"), format = ymd_hms
) %>%
activitylog(
case_id = "teacher_id",
activity_id = "teacher_action",
timestamps = c("start", "complete"),
```

```
resource_id = "teacher_name"
) %>%
to_eventlog()

# Cycle 3 - The teacher from Experiment Group 1
c3_e1 <- data %>% filter(class_name == 'c3_e1')
# Creating eventlog
c3_e1_eventlog <- c3_e1 %>%
# Rename timestamp variables appropriately
dplyr::rename(start = created_at, complete = updated_at) %>%
# Convert time format
convert_timestamps(
columns = c("start", "complete"), format = ymd_hms
) %>%
activitylog(
case_id = "teacher_id",
activity_id = "teacher_action",
timestamps = c("start", "complete"),
resource_id = "teacher_name"
) %>%
to_eventlog()

# Cycle 3 - The teacher from Experiment Group 2
c3_e2 <- data %>% filter(class_name == 'c3_e2')
```

```r
# Creating eventlog
c3_e2_eventlog <- c3_e2 %>%
# Rename timestamp variables appropriately
dplyr::rename(start = created_at, complete = updated_at) %>%
# Convert time format
convert_timestamps(
columns = c("start", "complete"), format = ymd_hms
) %>%
activitylog(
case_id = "teacher_id",
activity_id = "teacher_action",
timestamps = c("start", "complete"),
resource_id = "teacher_name"
) %>%
to_eventlog()

# Data visualization for Cycle 1 - Teacher E1
process_map(c1_e1_eventlog, type = frequency("absolute"))
process_matrix(c1_e1_eventlog, type = frequency("absolute")) %>% plot
animate_process(c1_e1_eventlog)

# Data visualization for Cycle 2 - Teacher E1
process_map(c2_e1_eventlog, type = frequency("absolute"))
```

```
process_matrix(c2_e1_eventlog, type = frequency("absolute")) %>% plot
animate_process(c2_e1_eventlog)

# Data visualization for Cycle 2 - Teacher E2
process_map(c2_e2_eventlog, type = frequency("absolute"))
process_matrix(c2_e2_eventlog, type = frequency("absolute")) %>% plot
animate_process(c2_e2_eventlog)

# Data visualization for Cycle 3 - Teacher E1
process_map(c3_e1_eventlog, type = frequency("absolute"))
process_matrix(c3_e1_eventlog, type = frequency("absolute")) %>% plot
animate_process(c3_e1_eventlog)

# Data visualization for Cycle 3 - Teacher E2
process_map(c3_e2_eventlog, type = frequency("absolute"))
process_matrix(c3_e2_eventlog, type = frequency("absolute")) %>% plot
animate_process(c3_e2_eventlog)
```

Appendix B

Transcripts of Teacher Interview in Cycle 1

[Awareness]

What are the perceptions of using this LA tool? (Interviewer)

As a teacher, I found that using the m-Orchestrate app to teach a lesson on the Eight Planets in the Solar System had several advantages. One of the main benefits was the ability to track student engagement and identify areas where students needed additional support. By analyzing data on student performance and engagement, I was able to adjust my teaching approach to provide more targeted support and clarification on challenging concepts. (Teacher E1)

[Continuity]

How did providing resources and feedback based on different learning trajectories benefit the students? (Interviewer)

The information generated by the LA tool did help me keep track of my students' inquiry status. Specifically, the tool allowed me to track how much time students spent on each activity and which activities they completed, which gave me a sense of how deeply they engaged with the material. In addition, I could see which students were struggling with specific concepts based on their performance on quizzes and assessments and provided additional support and guidance as needed. (Teacher E1)

I did find the LA tool to be helpful overall, there were times when the information it provided was not as useful for tracking student inquiry status. For example, the tool may not have captured the full extent of student engagement and understanding, as some students may have been more comfortable asking questions or engaging with the material in other ways. Additionally, there were limitations to the data types that could be tracked by the tool, which may have limited its ability to provide a complete picture of student inquiry status. (Teacher E1)

Is the information helping you well to provide resources and feedback? (Interviewer)

Yes, I did use information from the LA tool to provide resources and feedback to my students. For example, if the tool indicated that a particular student was struggling with a certain concept, I would provide additional resources, such as videos, readings, or practice problems, to help them better understand the material. I would also provide individualized feedback on assignments and assessments based on the data generated by the tool, highlighting areas where the student performed well and areas where they needed improvement. (Teacher E1)

However, if the LA tool did not provide any actionable insights or data that required intervention, I would not provide any specific resources or feedback based on its output. For example, it would be nice if the LA tool showed that most of my students struggle with a particular concept, such as the difference between inner and outer planets. Then I would adapt my teaching methods to provide more targeted support and clarification. (Teacher E1)

[Flexibility]

While I may not be modifying my teaching strategies on the fly in response to the data, the information from the LA tool can still be a valuable tool for ongoing assessment and improvement. By using it to monitor student progress and engagement, I can make informed decisions about how best to support their learning goals over time and adjust my teaching strategies as necessary to better meet their needs. (Teacher E1)

Appendix C

Domain Knowledge Quiz (Cycle 1)

<u>The Eight Planets in the Solar System</u>

Name: ______________ Student No.: ______________ Gender: Male/Female ____________

School: ______________ Class: ______________ Score: ______________

1. How many planets are there in the solar system? [C]

A. Six B. Nine C. Eight

2. Which is the only planet that appears to lie on its side? [A]

A. Uranus B. Saturn C. Neptune

3. The largest planet in the solar system is ________. [A]

A. Jupiter B. Earth C. Mars

4. The planet nearest Sun is _________. [C]

A. Mars B. Venus C. Mercury

5. Which is the only planet that has liquid water? [B]

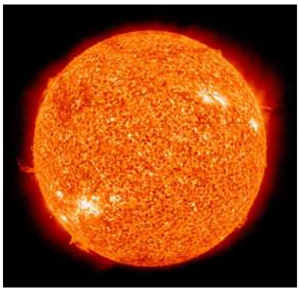
A. Mars B. Earth C. Venus

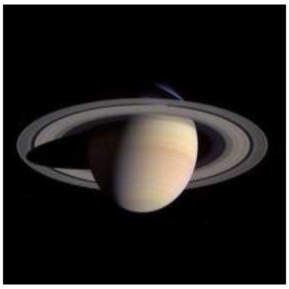
(con't)

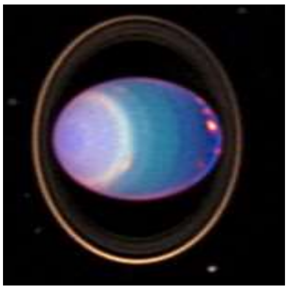
6. Match the following pictures of planets in the Solar system with their names.


a.


b.


c.


d.


e.

- Mars ___ [c] - Jupiter ___ [b] - Earth ___ [a] - Saturn ___ [d] - Uranus ___ [e]

7. The time taken for Earth to orbit Sun is _________. [D]

A. a day B. a month C. a season D. a year

8. The time taken for Earth to spin on its axis is _________. [A]

A. a day B. a month C. a season D. a year

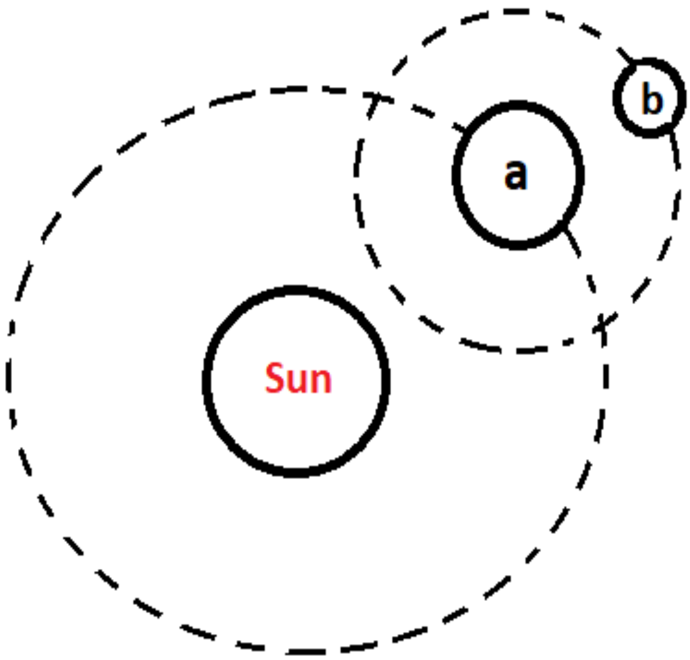
9. Sun rises in the _______ and sets in the _______. [A]

A. east; west B. south; east C. east; west D. north; east

(con't)

10. In the following diagram, ***a*** represents ________ and ***b*** represents ________. [B]

A. a star; a satellite B. a planet; a satellite C. D. a star; a comet



Thank you!

Appendix D

BupaR Source Code to Analyze Students' Log Data in M-Orchestrate

```
# Set working folder
setwd("~/R-mo-teaching")

# Install libraries
install.packages('plyr')
install.packages('bupaverse')
install.packages('processanimateR')

# Load libraries
library(plyr)
library(bupaverse)
library(processanimateR)

# 1. Data import
data <- read.csv('merge-csv.com__61288d5483956.csv', sep = ",", encoding = "UTF-8")

# 2. Data processing

# Exclude the clicking data without actual meanings
data <- subset(data, action != "stay active in an inquiry stage")
```

```
# Mapping values
data$phase <- mapvalues(data$phase,
from = c('1', '2', '3', '4', '5'),
to = c("Comment on log", "Open viewport", "Check detail", "Provide resources", "Provide feedback"))

# Total number of unique rows in the data file
nrow(unique(data))

# Overview of different classes
class_records <- split(data, data$class_name)

# Select specific classes from data set
smp_4b <- data %>% filter(class_name == 'SMP-4B')

# 3. Data transformation (change the data into eventlog)
smp_4b_eventlog <- smp_4b %>%
# Rename timestamp variables appropriately
dplyr::rename(start = created_at, complete = updated_at) %>%
# Convert time format
convert_timestamps(columns = c("start", "complete"), format = ymd_hms) %>%
activitylog(case_id = "group_id",
```

```
activity_id = "phase",
timestamps = c("start", "complete"),
resource_id = "group_name") %>%
to_eventlog()

# Properties of processed log data
smp_4b_eventlog %>% summary()

# 4. Data visualization

# Frequency: absolute, absolute_case, relative, relative_case
# Performance: median/mean, "years"/"semesters"/"quarters"/"
    months"/"weeks"/"days"/"hours"/"mins"/"secs"

process_map(smp_4b_eventlog, type = frequency("absolute"))

process_matrix(smp_4b_eventlog, type = frequency("absolute"))
    %>% plot

animate_process(smp_4b_eventlog)

dotted_chart(
smp_4b_eventlog,
x = "absolute",
```

```
sort = c("start", "end", "duration", "start_week", "start_day"
    ),
units = "weeks",
add_end_events = FALSE
)

idotted_chart(smp_4b_eventlog, plotly = FALSE)

# Remove duplicates from data
data <- unique(data)
```

Appendix E

Transcripts of Teacher Interview in Cycle 2

[Awareness]

What information did you notice from the LA tool? (Interviewer)

Regarding the information that bupaR could provide, it would depend on the specific parameters set for the tool. However, in general, bupaR is designed to help analyze data from various sources to identify patterns and insights related to student performance and engagement. It can be used to track student progress over time, identify areas where students may be struggling or excelling, and help teachers make informed decisions about how to support student learning best.(Teacher E1)

Using bupaR in the M-Orchestrate app, I was able to notice information such as student progress and engagement, areas where students may be struggling, and individual student needs and learning preferences. This information was helpful in shaping my pedagogical interventions and providing more personalized learning experiences for my students. (Teacher E2)

Please talk about your teaching experience of using the LA tool in the lesson. (Interviewer)

For teaching advantages, using bupaR could help me more accurately and efficiently monitor student progress and engagement and make data-driven decisions about how to adjust my teaching strategies to better meet their needs. For example, if the data indicates that a particular group of students is struggling with a specific topic, I could adjust my lesson plan to incorporate additional resources or activities that focus on that topic. (Teacher E1)

One advantage of using bupaR in the M-Orchestrate app was the ability to provide more personalized learning experiences for my students. By using data to understand their individual needs and preferences, I was able to create more tailored instructional materials and activities. Additionally, by monitoring student progress and engagement, I identified potential issues early on and intervened before they became more significant problems. However, there are also some potential disadvantages to consider, such as over-reliance on data, privacy concerns, and technical challenges in implementing and using the tool effectively. It’s important to be aware of these limitations and balance data and technology with other assessment and teaching strategies. (Teacher E2)

However, there are also potential disadvantages to using bupaR or any LA tool. For example, there is a risk of relying too heavily on data and overlooking the importance of individual student needs and preferences. It can also be time-consuming and challenging to set up and use the tool effectively, particularly if I do not have a strong background in data analysis. (Teacher E1)

[Continuity]

Did you provide resources and feedback according to some information from the bupaR? If yes, please specify what and how the information helped you shape pedagogical intervention(s)? (Interviewer)

Yes, I used information from bupaR to provide targeted resources and feedback to my students. For example, based on data about individual student progress and performance, I was able to provide specific resources and activities to support areas where they were struggling. I also used data on student engagement to provide timely feedback and encouragement, such as recognizing when students had completed certain tasks or showing appreciation for their contributions to class discussions. Overall, the data from bupaR helped me to shape my pedagogical interventions by allowing me to provide more personalized support and feedback to my students. (Teacher E1)

No, there were some instances where I did not provide resources and feedback based on the information from bupaR. This was usually because the data provided by bupaR did not align with other observations I had made about students' progress and understanding. In these cases, I relied on my own professional judgment to determine appropriate resources and feedback for my students. For example, there were times when bupaR indicated that a student had a low engagement with the lesson material, but upon further observation, I noticed that the student was engaged in other ways, such as asking thoughtful questions or participating in class discussions. In these cases, I provided feedback that was tailored to the student's strengths and needs rather than solely relying on the data provided by bupaR. Overall, while bupaR was a valuable tool in my teaching, it was not the sole source of information that I used to provide resources and feedback to my students. Rather, I used a combination of data, observations, and professional judgment to make informed decisions about how to best support my students' learning. (Teacher E2)

[Flexibility]

Did the information from the bupaR LA tool help you modify your teaching strategies on the fly? (Interviewer)

Yes, the information from bupaR was very helpful in allowing me to modify my teaching strategies on the fly. One example was when I noticed several students were struggling with a particular concept during a lesson. After checking the bupaR data, I saw that these students had consistently scored low on related practice exercises. (Teacher E1)

Based on this information, I modified my teaching strategies by providing additional examples and practice problems to help reinforce the concept. I also spent more time explaining the concept and checking for understanding among the struggling students. (Teacher E1)

In another instance, bupaR showed that a particular student was struggling with a specific aspect of the lesson. Using this information, I was able to modify my teaching strategy by providing more one-on-one support to this student during class and offering extra resources and support after class. (Teacher E1)

Yes, I did. The bupaR tool provided insights into the different learning trajectories of the students, which helped me tailor my teaching approach to each group's individual needs. (Teacher E2)

Can you give an example of how you provided targeted resources and feedback to a particular group of students? (Interviewer)

Sure, there was a group of students who were struggling with the concept of photosynthesis. Based on the insights from the bupaR tool, I provided additional resources, such as videos and articles, to help them better understand the concept. I also provided feedback that was tailored to the individual needs of each student in the group, such as providing specific examples or suggestions for improvement. (Teacher E2)

How did providing resources and feedback based on different learning trajectories benefit the students? (Interviewer)

By providing resources and feedback based on different learning trajectories, I was able to help each student achieve their full potential and improve their overall learning outcomes. Students were able to focus on areas where they needed the most support, which helped them feel more confident and engaged in the learning process. (Teacher E2)

Overall, what was your experience using the bupaR tool to provide targeted resources and feedback based on different learning trajectories? (Interviewer)

My experience using the bupaR tool to provide targeted resources and feedback based on different learning trajectories was positive. It helped me identify areas where students needed additional support and allowed me to provide targeted resources and feedback to help them achieve their learning goals. However, it also required a significant amount of time and effort to analyze the data and create personalized resources and feedback for each group of students. (Teacher E2)

Appendix F

Domain Knowledge Quiz (Cycle 2)

Plants

Name: _____________ Student No.: _____________ Gender: Male/Female ___________

School: _____________ Class: _____________ Score: _____________

1. The purpose of plant photosynthesis is?

A. Regulate water

B. Adapt to temperature

C. Store energy (correct answer)

2. What substances are needed as raw materials for plant photosynthesis?

A. Water, carbon dioxide (correct answer)

B. Water, oxygen

C. Water, starch

3. In what form is the energy absorbed by plants in photosynthesis usually stored in the body?

A. Sugar (correct answer)

B. Water

C. Protein

(con't)

4. Which of the following statements about plant growth conditions is correct?

A. The more light, the better the plant grows

B. Plants grow better in warmer places

C. Moist soil is conducive to seed germination (correct answer)

5. Under what conditions are plant seeds more likely to germinate?

A. Cold weather

B. Dry soil

C. Sufficient water (correct answer)

6. In addition to the factors listed in the textbook, have you learned about other external factors that affect plant growth in the process of inquiry learning? Please list them.

____

____

7. Seeds are generally hidden in what part of the plant?

A. Flower

B. Stem

C. Fruit (correct answer)

(con't)

8. Which of the following options is not a general function of plant root systems?

A. Fix plants

B. Absorb nutrients and water

C. Produce nutrients (correct answer)

9. Please observe the pictures of the plants below and list the structures and functions of the plants you know in the text box below the picture.

Thank you!

Appendix G

PyBKT Source Code

```
import numpy as np
import pandas as pd
from pyBKT.models import Model

# Define a function to calculate the mean absolute error
def mae(true_vals, pred_vals):
""" Calculates the mean absolute error. """
return np.mean(np.abs(true_vals - pred_vals))

# Initialize the model with an optional seed and number of fit initializations
model = Model(seed=42, num_fits=1, parallel=True)

# Fetch data and read the datasets
ct_df = pd.read_csv('/content/drive/Shareddrives/m-Orchestrate␣Implementation␣(2019-22)/Data␣analysis␣-␣pyBKT/merge-mo-data␣-␣copy␣-␣clean.csv', encoding='latin')
as_df = pd.read_csv('/content/drive/Shareddrives/m-Orchestrate␣Implementation␣(2019-22)/Data␣analysis␣-␣pyBKT/merge-mo-data␣-␣copy␣-␣as.csv', encoding='latin', low_memory=False)

# Fit the model on all skills
```

```
model.fit(data_path=ct_df)

# Evaluate the model with different metrics
metrics = {'rmse': 'rmse', 'auc': 'auc', 'mae': mae}
for name, metric in metrics.items():
training_score = model.evaluate(data=ct_df, metric=metric)
print(f"Training␣{name.upper()}:␣{training_score:.3f}")

# Fit the model on selected skills
skills = ['WeEngage', 'WeCollect','WeAnalyse','WeExplain','
    WeReflect']
model.fit(data_path=ct_df, skills=skills)
print("Fitted␣Skills:\n" + '\n'.join(model.coef_.keys()))

# Predict on test data
preds = model.predict(data_path=ct_df)
print(preds[['Anon␣Student␣Id', 'KC(Default)', 'Correct␣First␣
    Attempt', 'correct_predictions', 'state_predictions']].head
    (5))

# Test data proportion (i.e. 20% of all data used as testing
    data)
test_prop = 0.2
model = Model(seed=42, num_fits=1)
```

```
ct_data = ct_df

idx_split = np.array(ct_data.index.unique())
np.random.seed(42)
np.random.shuffle(idx_split)
training_data = ct_data.loc[idx_split[int(test_prop * len(idx_split)):]]
test_data = ct_data.loc[idx_split[:int(test_prop * len(idx_split))]]

training_data.reset_index(inplace=True)
test_data.reset_index(inplace=True)

skill = 'Calculate unit rate'
model.fit(data=training_data, skills=skill)

training_mae = model.evaluate(data=training_data, metric=mae)
training_auc = model.evaluate(data=training_data, metric='auc')
test_mae = model.evaluate(data=test_data, metric=mae)
test_auc = model.evaluate(data=test_data, metric='auc')

print(model.params())

```

```
print(f"Training Mean Absolute Error: {training_mae:.3f}")
print(f"Training AUC: {training_auc:.3f}")
print(f"Test Mean Absolute Error: {test_mae:.3f}")
print(f"Test AUC: {test_auc:.3f}")

config = {'multigs': True,
'multilearn': True,
'skills': ['WeEngage', 'WeCollect', 'WeAnalyse', 'WeExplain', 'WeReflect'],
'forgets': True,
'metric': 'accuracy',
'folds': 4,
'seed': 42 * 42}
model.crossvalidate(data_path='/content/drive/Shareddrives/m-Orchestrate Implementation (2019-22)/Data analysis - pyBKT/merge-mo-data - copy - as.csv', **config)
```

Appendix H

Transcripts of Teacher Interview in Cycle 3

[Awareness]

Hello! Can you tell me about your experience using pyBKT as a LA tool in the "Force, Motion, and Simple Machines" lesson you taught using the M-Orchestrate app? (Interviewer)

Sure, during the lesson, I used pyBKT to analyze student data on their understanding of the concepts. pyBKT provided me with information on how well students were able to grasp the different topics covered in the lesson. (Teacher E1)

That's interesting. Can you give me some examples of the advantages and disadvantages of using pyBKT in your teaching? (Interviewer)

One advantage is that pyBKT helped me identify areas where students were struggling and gave me insight into their misconceptions. This allowed me to adjust my teaching strategies in real-time and provide targeted support to those students who needed it most. Additionally, pyBKT gave me a better understanding of how each student learns and allowed me to customize my teaching approach to meet their individual needs. On the other hand, one disadvantage was that pyBKT required some time and effort to set up and analyze the data. It was also challenging to interpret the data accurately without the help of a data analyst. (Teacher E1)

That makes sense. Did you provide resources and feedback based on the information you received from pyBKT? (Interviewer)

Yes, I did. pyBKT helped me create personalized resources and activities for each student based on their learning trajectory. I also used the data to provide specific feedback to each student on their progress and understanding of the concepts. (Teacher E2)

That's great. Did pyBKT help you modify your teaching strategies on the fly? (Interviewer)

Absolutely. pyBKT gave me real-time feedback on how students were progressing, which allowed me to adjust my teaching strategies accordingly. For example, if I noticed that a large number of students were struggling with a particular concept, I could quickly change my lesson plan to provide more support and practice opportunities for that concept. (Teacher E1)

Lastly, did you provide resources and feedback to different groups based on their learning trajectories? (Interviewer)

Yes, I did. pyBKT provided me with information on each student's learning trajectory, which helped me group them based on their understanding of the concepts. I then provided targeted resources and feedback to each group to ensure they were getting the support they needed to succeed. (Teacher E2)

[Continuity]

Did you provide resources and feedback according to some information from the pyBKT? If no, please specify what and how. (Interviewer)

No, I did not provide resources and feedback according to the pyBKT tool. However, I still found the tool useful in identifying areas where students were struggling or excelling. This helped me to tailor my teaching strategies accordingly and provide more targeted instruction for those students who needed extra help or challenges. For example, I used the tool to identify topics that needed more classroom discussion or to group students based on their learning trajectory. Overall, the pyBKT tool provided valuable insights into my students' learning progress and helped me to make informed decisions about my teaching. (Teacher E1)

Did the information from the pyBKT LA tool help you modify your teaching strategies on the fly? (Interviewer)

No, the information from pyBKT did not significantly help me modify my teaching strategies on the fly. While the information was helpful in understanding each student's learning progress, I found that it did not always provide me with specific suggestions for how to modify my instruction. As a result, I still had to rely on my own pedagogical knowledge and experience to decide how best to engage and support my students. Additionally, I found that sometimes the information provided by pyBKT was not entirely accurate or reflective of each student's understanding, which made it challenging to make informed decisions about how to modify my teaching strategies. (Teacher E2)

Did you provide resources and feedback to different groups specifically based on different learning trajectories among different groups? (Interviewer)

While I didn't provide resources and feedback specifically based on different learning trajectories, I did use the information from pyBKT to inform my overall teaching strategies. For example, if I noticed that many students were struggling with a particular concept or skill, I would adjust my instruction to provide additional examples or explanations. I also used the pyBKT data to inform my lesson planning, ensuring that I was covering the most important concepts and skills in a way that was accessible to students. While I didn't provide individualized resources or feedback based on learning trajectories, I did use the data to make decisions that benefited the entire class. (Teacher E2)

Did you provide resources and feedback according to some information from the pyBKT? If no, please specify what and how. (Interviewer)

No, I did not provide resources and feedback according to the pyBKT tool. However, I still found the tool useful in identifying areas where students were struggling or excelling. This helped me to tailor my teaching strategies accordingly and provide more targeted instruction for those students who needed extra help or challenges. For example, I used the tool to identify topics that needed more classroom discussion or to group students based on their learning trajectory. Overall, the pyBKT tool provided valuable insights into my students' learning progress and helped me to make informed decisions about my teaching. (Teacher E2)

[Flexibility]

Did the information from the pyBKT LA tool help you modify your teaching strategies on the fly? (Interviewer)

Yes, the information from pyBKT did help me modify my teaching strategies on the fly. pyBKT provided me with real-time information on how well each student understood the material, which allowed me to adjust my instruction accordingly. For example, if I noticed that a particular student was struggling with a concept, I could offer additional support or guidance to help them better understand the material. On the other hand, if I noticed that a group of students had already mastered a concept, I could challenge them with more advanced questions or activities to keep them engaged and motivated. (Teacher E1)

Did you provide resources and feedback to different groups specifically based on different learning trajectories among different groups? (Interviewer)

Yes, I did provide resources and feedback to different groups based on their learning trajectories. pyBKT provided me with information about each student's knowledge state and progress throughout the lesson. Based on this information, I identified students who needed additional support and provided them with targeted resources such as extra practice problems or links to relevant online videos. I also gave individualized feedback to each student based on their performance and progress, which helped them understand where they were in the learning process and what they needed to focus on. This approach allowed me to differentiate instruction and meet the needs of each student, which is critical for promoting student learning. (Teacher E1)

Also, some passive voices toward pyBKT from the interviewees:

Did the information from the pyBKT LA tool help you modify your teaching strategies on the fly? (Interviewee)

No, the information from pyBKT did not significantly help me modify my teaching strategies on the fly. While the information was helpful in understanding each student's learning progress, I found that it did not always provide me with specific suggestions for how to modify my instruction. As a result, I still had to rely on my own pedagogical knowledge and experience to decide how best to engage and support my students. Additionally, I found that sometimes the information provided by pyBKT was not entirely accurate or reflective of each student's understanding, which made it challenging to make informed decisions about how to modify my teaching strategies. (Teacher E2)

Did you provide resources and feedback to different groups specifically based on different learning trajectories among different groups? (Interviewee)

While I didn't provide resources and feedback specifically based on different learning trajectories, I did use the information from pyBKT to inform my overall teaching strategies. For example, if I noticed that many students were struggling with a particular concept or skill, I would adjust my instruction to provide additional examples or explanations. I also used the pyBKT data to inform my lesson planning, ensuring that I was covering the most important concepts and skills in a way that was accessible to students. While I didn't provide individualized resources or feedback based on learning trajectories, I did use the data to make decisions that benefited the entire class. (Teacher E2)

Appendix I

Domain Knowledge Quiz (Cycle 3)

<u>Force, Motion and Simple Machine</u>

Name: _____________ Student No.: _____________ Gender: Male/Female ___________

School: _____________ Class: _____________ Score: _____________

1. Which of the following simple mechanical principles does scissors apply?

A. Roller

B. Slope

C. Lever (correct answer)

2. The point that supports the rotation of the lever is ________

A. Fulcrum (correct answer)

B. Force point

C. Center of gravity

3. Which of the following tools that apply the principle of lever can help users save effort?

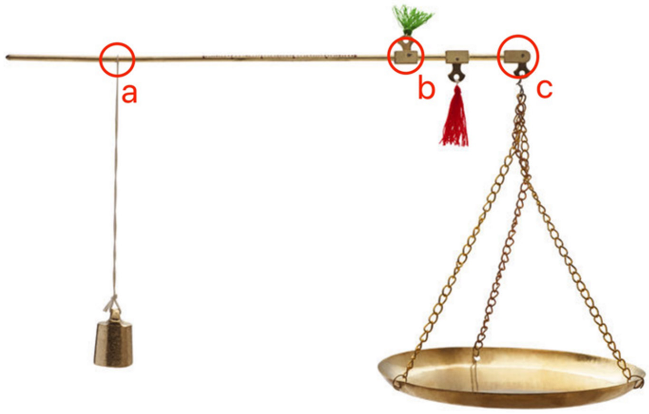
A. Tweezers

B. Chopsticks

C. Nail clippers (correct answer)

(con't)

4. Please indicate the position of the fulcrum in the figure below



A. Point a

B. Point b (correct answer)

C. Point c

5. If you want to help construction workers in high places, move heavy objects from low to high places, you should use ______ to enable workers to exert downward force and lift items, and use ______ to help workers save effort.

A. Movable pulley, fixed pulley

B. Lever device, movable pulley

C. Fixed pulley, movable pulley (correct answer)

6. Applying an external force on an object cannot change the object's ______.

A. Speed

B. Direction of movement

C. Gravitational force received from the earth (correct answer)

(con't)

7. Your friend wants to design a portable handcart for the elderly, which is convenient for them to carry heavy objects in their daily travel. What should he install at the bottom of the cart to achieve the effect of saving effort? [Single choice question] *

A. Roller (correct answer)

B. Fixed pulley

C. Slope

8. Which of the following methods can increase friction?

A. Pressing pits on the surface when making tires (correct answer)

B. Using smooth materials to make the surface of the slide

C. Adding lubricant at the pulley track

9. Please observe the picture of the crane working below, and list (1) which kind of simple machine is used by the parts shown by letters a and b and (2) briefly describe the effect of applying this mechanical principle.

____

____

Thank you!