Investigating the Role of a Conversational Artificial Intelligence Model in Promoting Self-Regulated Learning in Project-Based Learning for Software Engineering Students for Vocational Education

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Abstract

This PhD thesis investigates the integration of ChatGPT, a Conversational Artificial Intelligence (AI) model, into Project-Based Learning (PBL) environments to enhance Self-Regulated Learning (SRL) among software engineering students at V-Institute, a leading Vocational and Professional Education and Training (VPET) institution in Hong Kong. Employing a mixed-methods comparative design, the study combines quantitative data from the Motivated Strategies for Learning Questionnaire (MSLQ) and academic assessments with qualitative insights from interviews and ChatGPT logs. Findings reveal ChatGPT's comparable, slightly enhanced support for SRL compared to traditional PBL, with significant gains in effort regulation and help-seeking ($p<0.05$) and modest academic improvements ($p=0.041$). It fosters SRL through personalised guidance, debugging, and reflective reviews, supporting what are regarded as sophisticated projects aligned with industry standards. However, challenges such as dependency risks, technical limitations, and mixed teamwork impacts necessitate strategic curriculum design. The study proposes embedding AI literacy and prompt engineering to balance autonomy and collaboration, addressing VPET's resource constraints. Theoretical contributions enrich SRL and PBL frameworks, while practical implications advocate curriculum redesign for Hong Kong's higher and vocational institutes. Despite limitations such as the reliance on a single AI tool (ChatGPT), which may limit the generalisability to other AI models, the research highlights ChatGPT's transformative potential, offering a scalable, innovative approach to prepare students for AI-augmented workplaces while fostering critical thinking and industry-ready skills.

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Example:

AI	Artificial Intelligence
GPT	Generative Pre-trained Transformer
HD	Higher Diploma
HTML	Hypertext Markup Language
HTTP	Hypertext Transfer Protocol
Jakarta EE	Jakarta Enterprise Edition
JSP	Java Server Page
LLM	Large Language Model
MSLQ	Motivated Strategies for Learning Questionnaire
MVC	Model-View-Controller
PBL	Project-based Learning
SQL	Structured Query Language
SRL	Self-regulated Learning
TLP	Teaching and Learning Packages
VPET	Vocational and Professional Education and Training
VTC	Vocational Training Council

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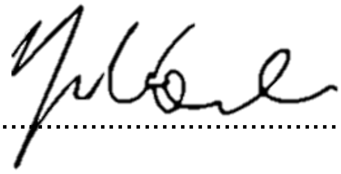

Publications derived from work on Doctoral Programmes

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Chapter 1: Introduction

1.1 Background of the Study

Hong Kong is a leading Asian city in the Information and Communication Technologies (ICT) sector with well-developed ICT talent pools and infrastructure. In the 2023 and 2024 policy addresses (HKSAR Government, 2023, 2024), the Hong Kong Government requested the need to consolidate its leading role. The city's policy is again further committed to invest resources to shape Hong Kong as an international innovation and technology hub.

The 2024 Manpower Update Report for the Electronics and Telecommunications Industries (Vocational Training Council, 2024) highlights a strong substantial demand for skilled ICT professionals. This stresses the important role of Hong Kong's universities and vocational education institutions in nurturing students, with both the practical skills and theoretical knowledge, that fits this market's needs. To achieve this, Project-Based Learning (PBL) has become an important educational strategy within these institutions. PBL is renowned for its practical learning approach, closely mirroring the real-world challenges confronted by ICT practitioners throughout their careers. Educational institutions, including the Vocational Training Council (VTC), have mandated the significant integration of PBL into curriculum, acknowledging its benefits. This approach aims to help students acquire practical experience and develop their 21st-century skills, such as effective problem-solving, communication, and collaboration, through engaging and collaborative projects.

In addition, the promotion of Self-Regulated Learning (SRL) in vocational education, particularly in software engineering, has been demonstrated to significantly improve students' capacities to independently manage their learning processes, thereby promoting greater adaptability and autonomy in dynamic work environments (Pintrich, 2000). PBL is suggested as a possible match to SRL, as PBL engages students in self-owned, real-world projects that require them to autonomously manage their learning processes. This can foster the development of critical skills, including goal setting, self-monitoring, and reflective evaluation. On the other hand, SRL equips students with the essential skills of setting objectives, monitoring their progress, and reflecting on their results among their project workers, all of which are essential for the ongoing learning that is necessary in the technology sector.

Nevertheless, despite the numerous advantages of PBL and SRL, the extensive implementation of these tools presents a number of challenges, particularly in terms of the need for students to develop strong SRL skills and resource constraints. Innovative and IT-based solutions to these constraints are sought by educators in order to achieve effective PBL, which necessitates substantial instructional resources and student support. This necessity motivates the investigation of sophisticated educational technologies, including Conversational Artificial Intelligence (AI), which have the potential to improve the efficacy of learning and expedite processes by offering personalised, scalable assistance (Ji et al., 2023; Qadir, 2023; Song et al., 2023).

New developments in AI, particularly Conversational AI powered by large language models (LLMs) like ChatGPT, have presented new possibilities for enhancing educational experiences, through interactive, personalised assistance; some research suggests they may support improved student engagement and fostering self-regulation in PBL activities (Adiguzel et al., 2023). Conversational AI systems can support the autonomous management of students' learning processes by offering personalised learning paths and prompt feedback, thus fostering essential SRL abilities vital for achievement in academic and professional settings. However, the utilisation of LLMs such as ChatGPT presents several issues and concerns that must be recognised. A notable drawback is the possibility of validity concerns in the data produced by AI. LLMs can generate information that is not consistently accurate or dependable, resulting in disinformation if students accept AI results without careful review (Bender et al., 2021). The problem can be made worse by the potential for promoting plagiarism, as students may be inclined to submit AI-generated text as their own without sufficient originality or critical analysis (Westfall, 2023). Moreover, there exists the issue of over-dependence on AI technologies. Students may develop excessive reliance on AI technologies for assistance, potentially compromising their own problem-solving capabilities and critical thinking skills. This dependence can obstruct the cultivation of vital skills necessary in practical environments (Selbst et al., 2019).

From an educator's viewpoint, these problems can contribute to uncertainty about using AI in instructional and learning methodologies. Concerns regarding the academic integrity and the genuineness of the educational experience may lead some educators to be cautious in fully incorporating AI tools into their courses (Anders, 2023). Addressing these problems necessitates careful evaluation and planned implementation to guarantee that AI enhances, rather than undermines, the educational community's objectives.

While there are opportunities and challenges linked to the integration of ChatGPT in education, as highlighted by Kirk (2023), tackling these challenges, as underscored by Passey (2021), is essential for achieving successful implementation and promoting favourable student outcomes. Integrating technology effectively requires deliberate planning and strategic curriculum design, ensuring that AI advancements contribute meaningfully to educational experiences.

1.1.1 Potential Educational Shift Driven by LLM

The use of LLMs is widely regarded as an unavoidable shift in societal development due to its strong ability to resolve several issues instantaneously. This mirrors earlier technology innovations, such as the use of calculators, computers, and the internet, which shifted our methods of problem-solving and education. Similar to how calculators became essential in mathematics education, computers could transform data processing and accessibility (Brynjolfsson & McAfee, 2014), while the internet altered the methods by which individuals obtained and disseminated knowledge (Newcomer, 2001). LLMs are said to be set to transform educational dynamics by providing immediate interactive assistance and customised learning trajectories (Chhibber & Law, 2021; Kowald & Bruns, 2019).

The essential factor is not merely the adoption of these new tools, but their application inside educational ecosystems. Thorough evaluation of educational methodologies and curriculum development is crucial to fully leverage AI technologies. Educators could integrate these tools to augment traditional teaching methods, akin to the incorporation of previous technological advancements, thereby equipping students for a future in which AI is important in their personal and professional spheres (Selwyn, 2019).

Some suggest that by using LLMs such as ChatGPT in a strategic manner, educational institutions could potentially address challenges and create new opportunities given the capacity of these potent tools in factual accuracy, reasoning, natural language process tasks, and instruction following. These abilities are evaluated by benchmarks like Measuring Massive Language Understanding (MMLU) in 57 subjects (86.4% for ChatGPT-4), HellaSwag for Commonsense reasoning around everyday events (95.3% for ChatGPT-4) and simulated college-level exams like Graduate Record Examination (GRE) (80~99th percentile for ChatGPT-4) and Scholastic Assessment Test (SAT) (89th~93th percentile for ChatGPT-4) (OpenAI, 2024). It signals ChatGPT's strength in delivering accurate, contextually responses across tasks. Therefore, LLMs, taking ChatGPT-4 as an example, are suggested to potentially support deeper learning, critical thinking, and innovative problem-solving skills among students, thereby enhancing the educational landscape and equipping learners for the complexities of the contemporary world.

This thesis investigates the role of a Conversational AI model, specifically ChatGPT, in enhancing SRL within PBL environments for software engineering students in vocational education. By integrating Conversational AI into PBL, the study aims to evaluate its impact on students' SRL capabilities and address challenges in effectively implementing PBL. Understanding the potential of Conversational AI to transform educational practices will provide valuable insights for educators and policymakers dedicated to improving vocational training in software engineering (Kulkarni et al., 2019). The findings may inform the design and implementation of PBL in software engineering curricula and facilitate the integration of AI technologies like ChatGPT into teaching practices at the higher diploma (HD) level. By exploring how ChatGPT supports SRL and enhances students' learning experiences, this study aims to contribute to ongoing efforts to improve the quality and effectiveness of Vocational and Professional Education and Training (VPET) for software engineering students, potentially benefiting other disciplines as well.

1.1.2 Vocational Educational in Hong Kong

Vocational education is a form of education aimed at equipping individuals with practical skills for specific trades. In Hong Kong, the development of VPET is a key driver for manpower development to meet the needs of a turbulent economy environment. The Hong Kong Government is committed to promoting VPET as one of the preferred educational pathways. It aims to enable young people to acquire future-ready work skills, applied knowledge in innovation and technology, and critical soft skills necessary for careers in the digital age, which can effectively nurture "masters of each trade" (HKSAR Education Bureau, 2015). Consequently, VPET plays an important role in broadening learning opportunities for both young people and working adults. It contributes significantly to Hong Kong's human capital development (HKSAR Education Bureau, 2020).

The Hong Kong government's policy focuses on providing quality, flexible, and diversified study pathways with multiple entry and exit points through VPET. This approach caters to individuals with different aspirations and abilities, ensuring accessibility and inclusivity. VPET offers programmes ranging from Applied Learning in secondary schools to HD programmes and Applied Degree programmes. Vocational curricula feature a high percentage of specialised content in occupational skills or professional knowledge (HKSAR Education Bureau, 2020).

Students engage with VPET from secondary school onwards, through diverse learning opportunities. A vibrant VPET sector supports this comprehensive approach. The sector includes a wide range of programme providers: universities funded by the University Grants Committee (UGC), post-secondary education and training institutions, and statutory bodies such as the VTC, Construction Industry Council, Clothing Industry Training Authority, and Employees Retraining Board. Additionally, the growing sector of corporate academies, the in-house training arms of industry corporations, further enrich the VPET landscape (Vocational Training Council, n.d.).

1.1.3 VPET and Integrating PBL into Curriculum

The VTC is the largest provider of vocational education and training (VPET) in Hong Kong, enrolling approximately 250,000 students annually through a range of pre-employment and in-service programmes. In view of the increasing demand for skilled workers in the labour market, the VTC has adopted PBL as a key strategy to deliver skills-based education. PBL is a practical teaching approach grounded in solving authentic problems, providing students with hands-on experience and real-world application of their knowledge.

In 2020, VTC set a plan to integrate PBL in teaching. The plan requires over 50% of the curriculum in HD programmes to be implemented through PBL. The goal is to achieve this target by 2024, following the principles of the Gold Standard PBL. This is a recognised framework that defines essential project design elements. This decision was driven by several key benefits from the VTC's perspective, according to the Vocational Training Council's Handbook on Conducting Project-based Learning (Vocational Training Council, 2020b).

Engaging Students in the Learning Process: PBL actively involves students in projects with real-life relevance. Students tackle problems related to their communities. This hands-on approach seeks to foster better engagement. Students are more motivated when they see the direct applicability of their work. Also, working on authentic tasks helps students develop a stronger connection to the subject matter. This can enhance their overall learning experience.

Raising Attainment and Promoting Deeper Learning: PBL involves sustained inquiry and investigation. This can lead to a deeper understanding and better retention of content knowledge, where students think critically and creatively. They can apply what they have learned to new and diverse situations. This depth of learning can help them transfer skills and knowledge beyond the classroom. It can prepare students for the complexities of the modern workplace.

Integrating Real-life Problems with Content Knowledge and Skills: PBL can bridge the gap between theoretical concepts and practical application. It engages students in collaborative, real-life problem-solving activities. This approach seeks to ensure that students are knowledgeable and capable of applying their skills in practical contexts.

Creating a Sense of Purpose: Successful projects can transform students by providing them with a sense of agency and purpose. They can gain confidence in their abilities by contributing to meaningful outcomes, recognising the value of their work. This empowerment can motivate them to take ownership of their learning, fostering a proactive attitude towards personal and professional development.

Seeing a Real-life Impact: PBL allows students to see tangible results of their efforts. They work on projects with real-world implications, understanding the impact of their contributions. This understanding can enhance their sense of achievement and satisfaction.

Developing Skills that Employers are Looking for: Employers seek individuals with both technical expertise and soft skills. These soft skills include teamwork, communication, problem-solving, and initiative. PBL can cultivate these competencies, placing students in collaborative environments where they navigate challenges, make decisions, and communicate effectively. PBL simulates workplace scenarios, preparing students to meet employer expectations and to excel in their careers.

However, VTC's widespread implementation of PBL presents challenges. These include having insufficient trained instructors, adequate facilities, involvement of external experts, and ongoing support mechanisms (Aldabbus, 2018). Lecturers must switch from traditional teaching methods to facilitative roles. They also need to guide students through complex projects and foster an environment conducive to self-directed learning.

To address these challenges, integrating innovative technologies into teaching, such as Conversational AI, can be a promising solution as tools like ChatGPT can provide personalised support to students, assist instructors in managing workload, and simulate multiple roles in a PB environment. By leveraging technology, VTC could address resource constraints and support the successful realisation of its strategic plan.

1.1.4 Emergence of Conversational AI in Education

In early 2024, VTC launched the ChatGPT platform for learning and teaching. This newly launched platform is accessible to all students. This initiative not only provides students with an intelligence learning companion, but also offers opportunities for innovation in teaching and learning to integrate advanced AI models into their curricula and pedagogical approaches. Considering PBL as the widely adopted educational strategy within VTC's curricula, it is worth investigating the benefit of incorporating ChatGPT in PBL facilitation.

Conversational AI technologies, including promising generative models like LLMs, exemplified by ChatGPT developed by OpenAI, have been proposed by some researchers as potentially transformative forces in the educational arena (Adiguzel et al., 2023; Limo et al., 2023; Waseem et al., 2024). These technologies employ advanced natural language processing capabilities to create interactive, human-like dialogue. It can offer students personalised assistance and feedback just like chatting with AI through an instant messenger. ChatGPT, in particular, showcases the potential of AI to understand and generate human-like text, providing a versatile tool for various educational purposes (Adiguzel et al., 2023).

LLM-powered tools are particularly promising in addressing the challenges associated with implementing PBL. PBL's focus on student-centred and experiential learning requires substantial guidance and feedback. It can be resource-intensive and take up a great deal of time from educators. ChatGPT can alleviate these challenges by offering immediate and personalised support that enhances student engagement and facilitates project management. That instant feedback and tailored learning resources can possibly support students' SRL processes, ensuring that PBL is more accessible and effective across diverse educational settings (Ji et al., 2023).

The integration of Conversational AI like ChatGPT is a potential candidate that can help facilitate and resolve problems associated with the implementation of PBL. These tools are stated to have potential to give learners the ability to manage their education actively, fostering a sense of agency and capability. Moreover, they can streamline many repetitive and time-consuming tasks, freeing educators to focus on more critical aspects of curriculum delivery and student interaction (Popenici & Kerr, 2017). As these technologies continue to evolve, there are possibilities to even further transform PBL implementations, enhancing accessibility and broadening educational opportunities by providing guidance as mentors or simulated authentication scenarios.

Furthermore, Conversational AI could potentially redefine instructional methodologies by facilitating adaptive learning environments that support diverse learner needs. This adaptability could not only support academic learning but also prepare students for the modern workforce by enhancing critical thinking, problem-solving, and communication skills.

Deploying ChatGPT across the VTC signifies a forward-looking approach to VPET. It opens an opportunity to employ AI to enrich educational content and improve learning outcomes in multiple dimensions. As more educational institutions acknowledge the potential of Conversational AI, these technologies may offer enhanced educational experiences and contribute to new teaching and learning paradigms in Hong Kong (J. Huang et al., 2024).

1.1.5 Project-Based Learning and Self-Regulated Learning

PBL is an educational strategy that engages students through real-life, meaningful projects, fostering deep learning and the development of essential skills. In VPET, PBL can bridge theoretical knowledge with practical application.

It can also prepare students for the workforce by mirroring real-world challenges (Barell, 2007). Through PBL, students are actively involved in problems that matter to their communities, promoting engagement by providing real-life relevance and offering a sense of purpose. This methodology not only has the possibility to raise attainment and support deeper learning but can also facilitate the retention of content knowledge, enabling students to apply learning effectively in varied contexts (Thomas, 2000).

In vocational settings, PBL is instrumental in developing attributes and skills that align with employer expectations, such as taking initiative, problem-solving, and collaboration. These are essential for navigating today's complex job environments, making PBL an invaluable component of vocational training programmes (Larmer & Mergendoller, 2010).

SRL is a valuable complement to PBL, emphasising the processes by which students self-manage their learning through goal-setting, self-monitoring, and reflection (Zimmerman, 2002). In PBL contexts, SRL is particularly significant as it supports students in managing the complexities of project tasks, fostering greater autonomy and motivation. Through SRL, students learn to take responsibility for their learning outcomes, enhancing their ability to integrate content knowledge with applied skills critically.

SRL encourages students to adopt learning strategies that promote active engagement, facilitating better understanding and retention of knowledge (Pintrich, 2000). This self-regulatory process is vital for the success of PBL, as it empowers students to navigate learning challenges independently, fostering a transformative educational experience that equips them with the skills needed for lifelong learning and career success (Pajares, 2008). Together, PBL and SRL provide a comprehensive framework for enhancing student learning outcomes in VPET, ensuring students are well-prepared to meet future professional demands.

1.2 Problem Statement

The problem statement for this PhD thesis focuses on addressing challenges within PBL contexts in the software engineering programme at a market-leading VPET institute in Hong Kong. As a programme leader, I face significant limitations concerning the allocation of time, human resources and limited sources of external parties who can be involved in facilitating student inquiries. These constraints not only make it challenging to meet the diverse needs of students, but consequently, these limitations impact the effectiveness and implementation of PBL. There are also obstacles affecting the progress for the success of widespread integration of PBL within the institute. It is increasingly difficult to maintain high-quality student engagement and inquiry in a resource-constrained environment (Barron & Darling-Hammond, 2008).

Furthermore, as a module lecturer, having the dual responsibilities of addressing numerous student enquiries and fulfilling administrative tasks intensifies these difficulties. The necessity of delivering prompt and comprehensive feedback to students frequently conflicts with administrative responsibilities, hence limiting the implementation and efficacy of PBL. These competing demands hinder the capacity to maintain a robust educational experience for students, ultimately affecting their learning outcomes and engagement levels (Cohen & Loten, 2014).

In this context, the potential of employing Conversational AI to mitigate these challenges has been under-explored. Conversational AI systems, recognised in some contexts for their ability to provide continuous, automated assistance (Azamatova et al., 2023; Limo et al., 2023; Qadir, 2023), may offer a promising solution to enhance PBL activities and SRL among students. The application of AI can effectively streamline responses to student inquiries around the clock, thus alleviating some of the workload from educators and providing consistent student support (Adiguzel et al., 2023). Nevertheless, the literature, which will be presented in the next section, highlights a gap concerning how Conversational AI can be effectively incorporated into PBL frameworks to improve resource utilisation and enhance student engagement.

This research seeks to explore this untapped potential of Conversational AI in bolstering both PBL and SRL. It aims to develop a comprehensive framework that not only enhances educational outcomes but also optimises the use of available resources. By integrating AI into PBL environments, the study proposes pathways for overcoming existing challenges, thereby fulfilling the educational mandate of integrating PBL more deeply and effectively within vocational education for software engineering students.

Thus, the focus of this thesis is to investigate strategic methodologies by which Conversational AI can be leveraged to transform the learning landscape in VPET. This involves examining the ways AI tools can mitigate current challenges and facilitate more effective implementation of PBL methodologies, ensuring that students can benefit from a richer, more supportive learning experience (Kulkarni et al., 2019).

1.3 Research Objectives

This study's research objectives are designed to comprehensively investigate the incorporation of Conversational AI into PBL and assess its impact on SRL among software engineering students in vocational education. The project seeks to examine how Conversational AI might impact the PBL experience, driven by the necessity to improve educational results and tackle problems in PBL implementation, including resource limitations, instructor readiness, and diverse levels of student self-regulation. These objectives establish a complete framework for inquiry, facilitating an in-depth analysis of the potential advantages, practical applications, and ramifications of employing Conversational AI to enhance SRL. The project aims to provide significant insights for educators, policymakers, and the wider research domain of educational technology through three objectives.

Evaluating the impact of AI-supported PBL on students' SRL compared to traditional PBL

This objective seeks to evaluate the impact of Conversational AI, such as ChatGPT, on SRL processes, including goal formulation, self-monitoring, and reflection, in contrast to traditional PBL environments. The assessment will assess the efficacy of AI technology in promoting self-regulation and involving students in their learning processes, as suggested by Zimmerman (2002) within the framework of SRL theories and techniques.

Identify how Conversational AI can resolve challenges in PBL implementation

This objective aims to investigate how Conversational AI can resolve challenges encountered in PBL implementation, including the management of student enquiries and the provision of prompt feedback. The research also examines the potential of AI tools to improve educator efficiency by functioning as virtual teaching assistants, alleviating burden, and providing ongoing support to students (Adiguzel et al., 2023). This may enable a smooth incorporation of technology into teaching methodologies, enhancing a more comprehensive PBL framework.

Explore students' perceptions of using Conversational AI in PBL activities

This objective seeks to collect insights regarding students' experiences and perceptions of Conversational AI in PBL. Comprehending students' perceptions will reveal the perceived advantages and possible disadvantages of AI integration, informing enhancements in its implementation. Student involvement and acceptance are essential for the effective implementation of educational technology, as indicated by Kulkarni et al. (2019), who highlight the significance of user-centred design and feedback in the adoption of educational technology.

Through these objectives, the study aims to inform the understanding of Conversational AI's role in enhancing PBL and SRL, offering insights for VPET educators and policymakers dedicated to improving pedagogy and outcomes. By addressing these objectives, the study aims to contribute to the growing body of research on technology-enhanced learning, providing actionable insights for incorporating AI solutions in VPET effectively. The findings will inform strategies to leverage AI tools not only to augment traditional learning methods but also to empower students in their educational journeys.

1.4 Research Questions

This study investigates the integration of Conversational AI, specifically ChatGPT, within PBL frameworks to enhance SRL for software engineering students. The research also studies the impact of AI on student engagement, outcomes, and challenges in VPET, aiming to inform future educational strategies and innovations. Consequently, the study's research question and sub-questions are:

Main RQ: How does the use of ChatGPT in project-based learning impact software engineering students' self-regulated learning?

This question seeks to explore the relationship between the integration of ChatGPT as an educational tool and its effects on students' SRL processes. SRL encompasses various dimensions, including goal setting, self-monitoring, and strategic planning (Zimmerman, 2002). Understanding this relationship is crucial for developing effective educational practices that leverage AI technologies. Followed by the primary RQ, there are four sub-questions with corresponding hypotheses.

RQ 1.1: How can ChatGPT be integrated into Project-Based Learning (PBL) environments to support the development of the key components of self-regulated learning among software engineering students in vocational education?

Hypothesis 1.1: The integration of ChatGPT into PBL environments will enhance students' goal-setting and self-monitoring abilities to a similar or improved extent compared to traditional learning methods. This hypothesis aligns with findings that suggest AI tools can facilitate personalised learning experiences, fostering similar or improved engagement and self-regulation. To indicate the improvement, statistical analysis of MSLQ scores is employed to look into the improved performance, supported by inferential statistics like p-value and Cohen's d.

RQ 1.2: What are the perceived benefits and challenges of using ChatGPT in PBL settings for software engineering students?

Hypothesis 1.2: Students will report a range of perceived benefits from using ChatGPT, including improved access to information and enhanced problem-solving capabilities. However, challenges such as reliance on AI for answers may also be identified. Previous studies indicate that while AI tools can support learning, they may also lead to dependency issues (Alonso-Nuez et al., 2024; Hasanein & Sobaih, 2023; Limo et al., 2023; Schönberger, 2023).

RQ 1.3: How does the integration of ChatGPT in PBL environments impact software engineering students' problem-solving, teamwork, and communication skills?

Hypothesis 1.3: Students who use ChatGPT will demonstrate improved problem-solving skills and enhanced collaboration in team projects compared to those who do not use the tool. Research suggests that AI can augment collaborative efforts by providing instant feedback and facilitating communication among team members (Waseem et al., 2024).

RQ 1.4: What are the implications of integrating ChatGPT into PBL settings for the curricula in vocational education institutions in Hong Kong?

Hypothesis 1.4: The integration of ChatGPT into curricula will lead to positive changes in instructional practices, including increased use of technology-enhanced learning methods. This hypothesis reflects a growing recognition of the need for educational institutions to adapt their curricula to incorporate emerging technologies effectively (Hasanein & Sobaih, 2023).

The proposed sub-questions address various aspects of the main research question, which focuses on the utilisation of ChatGPT to promote SRL in PBL environments for software engineering students in vocational education. The first sub-question focuses on the key components of SRL, providing a foundation for understanding the elements that need to be considered when incorporating ChatGPT in PBL settings among software engineering students. It also explores how ChatGPT can be integrated into PBL environments to support the development of SRL skills among software engineering students, offering insights into the practical application of the AI tool. The second sub-question examines the perceived benefits and challenges of using ChatGPT in PBL settings from the perspectives of students, shedding light on potential facilitators and barriers to successful implementation. The third sub-question investigates the impact of ChatGPT integration on students' problem-solving, teamwork, and communication skills, which are essential outcomes of PBL (Hmelo-Silver et al., 2007). Finally, the fourth sub-question considers the practical implications of integrating ChatGPT into PBL settings for software engineering curricula in vocational education institutions, providing guidance for educators and policymakers (Luckin et al., 2016).

By addressing these questions, the research aims to provide insights into how best to support students' learning and development in PBL contexts, as well as to contribute to the understanding of how Conversational AI systems can be used to support SRL.

1.5 Significance of the Study

This study offers multiple value through its contributions to theoretical, practical, and technical realms in education and beyond. Theoretically, it intends to advance our understanding of how digital tools facilitate SRL. Practically, it seeks to provide educators with insights into the practical application of AI to enhance pedagogical strategies and curriculum design. Technologically, it aims to inform the development of AI systems specifically tailored to educational settings, thereby enhancing learning accessibility and personalisation.

1.5.1 Theoretical Significance

The theoretical significance of this study is rooted in its focus on integrating Conversational AI with PBL to enhance SRL, contributing to existing educational literature. In this context, a growing body of research has begun to explore the use of ChatGPT in PBL, including observing how students employed LLM in a PBL setting. It has also identified both potential benefits and drawbacks of chatbots in educational settings. The wider potential of employing Conversational AI to address the implementation, the factors to enhance students' PBL experience and SRL, as well as the challenges, remain under-explored. These are presented in Chapter 2 through a detailed literature review. Conversational AI systems, known in various contexts for their ability to provide continuous, automated assistance, may offer a promising avenue for enhancing PBL activities and supporting SRL among students. SRL is a critical factor in student success, emphasising self-guided behaviours such as goal setting, self-monitoring, and strategic learning (Zimmerman, 2002). This study can contribute to the theoretical frameworks by providing empirical evidence on the efficacy of Conversational AI tools like ChatGPT in facilitating these self-regulation processes within PBL settings.

By investigating this integration, the study extends the theoretical boundaries of how digital tools can empower students to develop critical learning strategies, enhancing their autonomy and capacity for self-reflection (Schunk & Zimmerman, 2008). This intersection of technology and education may herald a rethinking of pedagogical practices, indicated by exploratory research on incorporating AI, such as ChatGPT, into PBL (Zheng et al., 2024). However, additional empirical inquiry is needed to clarify precisely how much a shift can be realised in classroom, especially as the literature also highlights challenges and ethical considerations associated with AI use in education.

Furthermore, by contextualising the research within vocational education, the study provides valuable insights into aligning educational technologies with practical and applied learning goals, ensuring that technological advancements translate into meaningful educational outcomes (Pintrich, 2004). This contributes to highlighting how technology can be leveraged to enhance teaching efficacy and learner engagement in diverse educational contexts (Greene et al., 2018). Through these theoretical contributions, the study seeks to advance our understanding of the potential for AI to inform new educational strategies, promoting lifelong learning skills essential for the 21st century.

1.5.2 Practical Significance

This study aims to offer insights for educators looking into the practice of employing Conversational AI tools in enhancing PBL. By tackling challenges like time limitations and resource constraints, and by enhancing student engagement, the research will outline practical strategies that teachers can use to bring new technologies into their teaching methods. This approach will be especially important for helping educators manage their workload while maintaining the quality of student interactions, thereby promoting better educational outcomes such as enhanced student engagement, deeper conceptual understanding and improved academic performance (Adiguzel et al., 2023).

Additionally, findings from this research have the potential to influence curriculum development within vocational education settings. By demonstrating how AI can be strategically employed to respond to the evolving demands of both learners and the workforce, the study guides educational institutions in embedding AI technologies into their curricula in a way that aligns with 21st-century skills requirements (Kulkarni et al., 2019). This approach positions Conversational AI as a promising tool in advancing educational practices and preparing students for the challenges of modern workplace environments.

1.5.3 Technological Significance

From a technological perspective, this study will offer pivotal direction in guiding the development of educational conversational tools tailored to the complexities of vocational education. By concentrating on the specific needs and challenges faced in this field, the research may provide insights into developing responsive and supportive learning resources. These advancements could help shape the educational landscape, potentially offering more accessible and personalised learning opportunities for students across various vocational disciplines (Ji et al., 2023).

This study will explore how new technologies may address educational needs and support technology-based methods. By showing how conversational tools might improve learning through personalised interaction and immediate feedback, the research could suggest these tools as potentially beneficial for advancing education. This move towards technology-enhanced learning envisions a future where educational environments are designed to meet each student's specific needs, creating a more engaging and effective experience (Kulkarni et al., 2019).

The study may also inform technological discourse, by suggesting approaches for integrating AI technologies into education frameworks. This focus may underscore the potential for educational AI systems to facilitate teaching practices and support student learning experiences, thereby bridging the gaps between theoretical concepts and practical implementation in vocational education.

This research aims to contribute to the ongoing evolution of educational technology, paving the way for the adopting of AI-driven solutions that enrich the educational process, support educators, and empower students, each of whom plays a vital role in shaping a technologically adept future (Popenici & Kerr, 2017).

1.6 Scope and Delimitations

1.6.1 Scope

The scope of this study is specifically focused on evaluating the role of Conversational AI, particularly ChatGPT, in enhancing SRL within PBL environments for HD in Software Engineering students of a Hong Kong leading VPET institute named "V-Institute" in this study. The V-Institute mainly offers HD programmes, a kind of sub-degree vocational programme. To follow the institute's strategic plans on widespread adoption of PBL, the programme curricula are revised to integrate more than 50% of PBL components into their modules. In addition, V-Institute further requires adopting 50% to 70% PBL components among newly developed programmes. This arrangement makes the institute an ideal candidate for examining the integration of Conversational AI in PBL lessons. The research is conducted at the Department of Information

Technology of the institute's Sha Tin campus, where the HD in Software Engineering programme is developed and delivered.

This study is dedicated to systematically examining how ChatGPT can be seamlessly integrated into PBL activities to enhance SRL among software engineering students, situated within the educational framework of the V-Institute, where ChatGPT is widely accessible to all students and staff for teaching and learning. The research will investigate its effects on student engagement, learning outcomes, and self-management skills. While ChatGPT provides a promising avenue for supporting learning in this context, it is crucial to acknowledge that the study's concentration on this specific AI tool does not fully capture the breadth of capabilities or limitations associated with other Conversational AI technologies. Therefore, while ChatGPT is utilised as a model for AI integration in education, the findings will primarily pertain to this technology and its application within these vocational education settings.

Furthermore, the study is inherently context-specific, focusing on VPET within the unique educational setting of Hong Kong. This specificity may limit the generalisability of its findings to other disciplines, higher educational contexts, or cultural backgrounds, as highlighted by Creswell and Plano Clark (2011). This specificity underscores the importance of considering local educational frameworks, cultural nuances, and institutional priorities when interpreting and applying the outcomes of this research. It serves as a foundation for understanding how AI technologies, like ChatGPT, can be effectively employed in educational environments characterised by resource constraints and diverse learner needs.

To ground this investigation, the study introduces a selected module within the HD in Software Engineering programme, where ChatGPT will be integrated into the PBL components. This module, "Enterprise System Development", is designed to leverage the capabilities of Conversational AI to support student learning and project development processes. By employing ChatGPT, students will have access to real-time feedback and guidance, potentially enabling them to engage more deeply with project tasks, enhance their SRL skills, and better understand complex software engineering concepts.

This module provides a practical context for investigating the role of Conversational AI in enhancing educational practices, with a particular focus on the potential for improving student engagement and learning outcomes in PBL settings. It offers a structured environment for students to explore the dynamic interaction between AI tools and their learning processes, thus contributing data to the ongoing discourse on modernising educational practices in software engineering and beyond.

Through this integration of Conversational AI within a specific curriculum module, the study aims to contribute insights into the broader role of AI in vocational education workflows. It lays the groundwork for future research exploring the scalability and adaptability of these approaches across different educational contexts and disciplines, ultimately enriching the educational landscape with evidence-based methodologies.

1.6.2 Delimitation

The delimitation sets the boundaries for the research, defining the scope and parameters within which it will be conducted. Geographically, the study is confined to the Hong Kong context, specifically within a marker leader VPET institute. This deliberate choice aligns with Hong Kong's educational system and institutes' operations, which can potentially extend the findings of this study to other Hong Kong higher institutes sharing the same geographical context.

The study is conducted within a VPET setting, primarily targeting students at the sub-degree level pursuing a HD in software engineering. This focus ensures that the research is contextually relevant and tailored to the unique educational and training environments that characterise VPET settings, where practical, hands-on learning is emphasised alongside academic achievements.

The study focuses on ChatGPT, as it is the AI tool made available to students and staff among most higher institutes in Hong Kong (Cheng & Yim, 2024).

Beyond specific AI tools, Conversational AI as a broader category holds the potential to offer general solutions across various disciplines, effectively addressing diverse challenges and serving as a medium for inquiry in PBL (Fryer et al., 2020). As ChatGPT is currently utilised within VTC environment, this study presents an opportunity to systematically explore and document its use to enhance teaching and learning in VPET.

Furthermore, the research deliberately narrows its focus to the integration of Conversational AI, specifically ChatGPT, within PBL frameworks, intentionally excluding other forms of AI or educational technologies not directly linked to conversational interactions. This targeted approach allows for a concentrated examination of how Conversational AI impacts SRL and enhances educational outcomes specifically in the realm of software engineering. By homing in on ChatGPT, the study seeks to provide actionable insights that can inform best practices for leveraging this tool in VPET contexts. This focus is poised to contribute to improved educational methodologies and facilitate enriched student learning experiences tailor-made for the demands of VPET.

The study centres its investigation on a single practical module within a HD programme: “Enterprise System Development”. This module was chosen for its strong alignment with PBL and its direct applicability to software engineering tasks. By concentrating on a practical subject, the study aims to elucidate how ChatGPT can specifically support project tasks and student learning in applied settings. In contrast, the study neither aims to integrate the use of ChatGPT from a holistic programme design perspective, nor does it extend its investigation into more theoretically oriented modules such as mathematics, data structures, and algorithms. These subjects, often foundational and abstract, are typically less dependent on Conversational AI’s interactive feedback capabilities and thus fall outside the study’s scope.

By maintaining this focused analysis, the research aims to provide detailed insights into how Conversational AI can be effectively implemented within practical learning environments to enhance SRL. These insights will serve as guiding principles for educators seeking to incorporate AI tools in vocational subjects, ensuring that educational practices remain relevant to the skills and demands of today's technological workforce. This approach also ensures that the findings remain specific and actionable, offering clear pathways for applying AI technologies in educational settings that prioritise hands-on, experiential learning.

The study acknowledges potential challenges, such as obtaining a representative sample of students within this focused setting, which could influence the validity and reliability of its findings (Bryman, 2016). Additionally, reliance on self-reported data from participants poses risks of biases, including social desirability and recall bias, which may affect study conclusions (Podsakoff et al., 2003). Despite these limitations, the research explores implications for enhancing software engineering education and advancing the effective use of Conversational AI systems to support SRL. Future studies can build upon this research by addressing these delimitations and expanding the investigation to broader educational contexts.

1.7 Organisation of the Thesis

This thesis is divided into five chapters. In addition to this introduction chapter, the remaining four chapters include the Literature Review, Research Design, Findings and Discussion, and Conclusion, Implications, and Reflections.

Chapter 2: Literature Review

Chapter 2 provides a review of the existing literature related to the key themes of the study. It begins by exploring the theories, practices, and challenges of PBL. Subsequently, it explores the theories and practices of SRL. Following this, the applications of Conversational AI in education are analysed. The literature review also investigates the interconnections between PBL, SRL, and Conversational AI, leading to the identification of the research gaps addressed in this study.

Chapter 3: Research Design

This chapter describes the methodology for investigating AI integration in PBL. A comparative design evaluates its impact on vocational software engineering students in traditional and AI-supported PBL settings. It details data collection, combining quantitative SRL measures with qualitative student perceptions. The implementation of Conversational AI-supported PBL, analytical techniques for assessing outcomes, ethical considerations, and measures for study validity and reliability are also discussed.

Chapter 4: Findings and Discussion

This chapter summarizes the study's findings on AI's impact on students in a PBL environment. Quantitative data, including pre- and post-test MSLQ results and academic performance, assess self-directed learning behaviours in students using AI versus those who did not. Qualitative data from observations and semi-structured interviews explore AI's influence on PBL experiences. The results are cross-referenced for validation, providing insights into how AI affects student performance and learning strategies.

Chapter 5: Conclusions, Implications, and Reflections

The final chapter summaries the key findings and articulates the contributions of the study to VPET and educational technology. It reflects on how the integration of Conversational AI can address challenges in PBL implementation and promote SRL among students. The chapter discusses the theoretical and practical implications, offers recommendations for educators and institutional policymakers. It also suggests areas for future research. Limitations of the study are acknowledged, and personal reflections on the research journey are shared, highlighting the potential for ongoing developments in leveraging AI to enhance educational outcomes.

Chapter 2: Literature Review

To explore potential improvements in educational practices for software engineering in VPET, it is essential to investigate pedagogical tactics and technical tools that may positively influence student learning outcomes. This literature review aims to present a comprehensive overview of the theoretical and empirical underpinnings related to PBL, SRL, and the use of Conversational AI in education. The review seeks to synthesise existing research to identify potential intersections among these areas and propose a framework for integrating Conversational AI to support SRL in PBL environments.

The literature review process was conducted using three search platforms, Elicit, Google Scholar and Scopus. These tools were selected for their comprehensive coverage of academic publications and Elicit's AI ability to identify relevant research through LLM. Documents were also searched from the Hong Kong Education Bureau and Hong Kong Vocation Training Council for localised Hong Kong context and government policy. Search terms included combinations of keywords in several key categories including pedagogical approaches ("project-based learning", "PBL"), learning strategies ("self-regulated learning", "SRL"), artificial intelligence technologies ("ChatGPT", "LLMs", "AI in education", "chatbots"), domain applications ("AI for computer science education", "AI for software engineering study", "AI for STEM"), and educational contexts ("vocational education", "higher education"). Additionally, compound searches were performed using combinations such as "PBL and SRL", "ChatGPT for PBL", and "AI for self-regulated learning". This systematic search yielded approximately 850 potential sources. The selection criteria prioritised recent publications (from 2015-2025), articles with significant citations counts when available, and relevance to post-secondary educational contexts. Papers were excluded if they were retracted, focused on preschool or K-12 education without direct relevance to PBL or STEM fields. The screening process resulted in 174 sources that formed the foundation of this review. The selected literature represents current knowledge in PBL, SRL strategies and AI technologies enhanced teaching and learning in educational and VPET context.

The chapter begins by discussing the concepts and methodologies of PBL, highlighting its role in vocational education and its potential to develop practical skills in software engineering students. It then explores the notion of SRL, focussing on the cognitive and metacognitive processes that enable learners to learn to manage their own learning. The section further explores the role of Conversational AI, such as chatbots, in educational setting, considering how AI-driven conversational agents may support teaching and learning processes.

Building on these foundational concepts, the review investigates how Conversational AI might be integrated into pedagogies such as PBL and SRL. This section examines existing studies and theoretical frameworks that combine these elements, assessing the potential impact of Conversational AI on SRL within PBL environments. The analysis identifies gaps in current research, including limited exploration of Conversational AI's roles in vocational education, particularly within the software engineering field.

The concluding section synthesises key findings from the literature to outline specific areas requiring further investigation. It underscores the need for empirical research on how Conversational AI could be integrated into PBL environments to support SRL among software engineering students. This gap in the literature provides a basis for the current study, which aims to address these questions and contribute to the existing knowledge in this field.

This chapter systemically reviews and critiques the current literature, providing a foundation for the research methods and analysis presented in the subsequent chapters. It contextualises the study's relevance and supports the rationale for the chosen research focus, guiding further exploration of how Conversational AI may facilitate SRL within PBL frameworks.

2.1 Project-based Learning (PBL)

PBL is an instructional approach focused on student-driven inquiry and hands-on projects, often designated to tackle real-world challenges. This method tends to emphasise collaboration, problem-solving, and critical thinking, and it provides opportunities for students to engage in active learning environments that mirror aspects of real-world complexity (Gao & Yang, 2023). PBL is rooted in experiential learning theories, which propose that knowledge is constructed through active participation and the practical application of ideas.

Education in STEM fields often employs PBL due to its potential to connect theoretical concepts with practical skills, which may be particularly relevant in the context of engineering education (Lei, 2014). Through projects designed to reflect industry-like tasks, it has been shown that PBL can help students develop skills such as coding, debugging, and software design which are often considered valuable for engineering students. Beyond technical skill development, PBL also provides opportunities for teamwork, as students work together to address complex challenges, potentially strengthening their communication and cooperative learning abilities (Gary, 2015).

The PBL framework appears adaptable to diverse educational objectives, which may contribute to its broad use across different disciplines. It seems to align with the constructivist educational theory, suggesting that learners build new understanding through their experiences and interactions (Funke, 2022; Kokotsaki et al., 2016; Mosier et al., 2016). For educators implementing PBL, guiding students in managing their projects could be important to ensure the learning process remains constructive and consistent with curriculum goals (Simbolon, 2016).

In vocational education settings, like those found in Hong Kong, PBL may offer particular advantages. It could equip students with skills and knowledge that correspond to industry expectations, potentially aiding their preparation for workforce demands (Vocational Training Council, 2020b). This approach might also foster greater academic engagement while encouraging autonomy and responsibility in learners, which are qualities often associated with SRL.

In summary, PBL's focus on real-world application, collaborative learning, and critical thinking suggests it could serve as a useful instructional strategy in contemporary education. Its flexibility may allow it to address the changing needs of educators and students, potentially providing learners with skills that support success outside the classroom (Aldaberdikyzy & Berdibay, 2021).

2.1.1 Theoretical Foundations of PBL

The theoretical foundation of PBL is closely tied to the constructivist and experiential learning paradigms, which have played a notable role in influencing modern educational practices. Drawing from the work of John Dewey (1938), experiential learning suggests that education can be more effective when rooted in active problem-solving and real-life experiences. Dewey proposed that learners might construct knowledge more readily through engaging, hands-on activities that resemble real-world challenges, highlighting the potential value of learning through direct experience (Simbolon, 2016).

A key element of PBL seems to align with Lev Vygotsky's (1981) social constructivist theory, which emphasises the role of social interactions in cognitive development. Vygotsky's concept of the Zone of Proximal Development (ZPD) suggests that individuals learn effectively when they work collaboratively with others, particularly when supported by more knowledgeable peers or mentors. This collaborative aspect appears integral to PBL, where students often participate in group projects that could foster the exchange of diverse perspectives and collective problem-solving (Allan, 2007).

Cognitive psychology further informs the framework of PBL, with Ambrose and colleagues (2010) underscoring several principles that advance deep learning. These principles include the need for motivation through relevance, support for active learning, and the cultivation of SRL practices. PBL seems to incorporate these elements by involving students in meaningful projects that encourage active exploration and self-direction, potentially narrowing the gap between theory and practice (Niewoehner et al. 2011).

Moreover, PBL appears designed to foster essential 21st-century skills. In the VTC's (2020) perspective, 21st-century skills are necessary for success in an increasingly complex and interconnected world. Skills such as critical thinking, creativity, collaboration, and communication are cultivated through PBL's emphasis on interdisciplinary projects that require students to navigate and integrate multiple domains of knowledge (Poell et al., 1998). This approach might not only prepare students for academic success but could also equip them with the competencies needed to address multifaceted global issues.

In vocational education, in fields like software engineering, studies have found that PBL aligns educational outcomes with industry standards by simulating professional environments and challenges (Gary, 2015). This alignment ensures that students acquire both theoretical understanding and practical skills, enhancing their employability and readiness for the workforce (Vocational Training Council, 2020b). By incorporating authentic tasks that mirror workplace scenarios, PBL could ease the transition from academic settings to professional careers.

Studies ascertain that the adaptability of PBL to various educational settings and objectives accounts for its widespread application (Nilson, 2010) and scalability (Mantri, 2014). This flexibility allows educators to tailor learning experiences to specific contexts, thereby supporting diverse needs (Doppelt, 2003). This adaptability reinforces PBL's role in fostering independent, self-directed learners who are prepared to tackle complex problems with confidence and creativity (Saidova & Ergasheva, 2019).

In summary, the theoretical foundation of PBL appears to blend constructivist, social, and cognitive theories, suggesting a dynamic educational model that aligns with modern pedagogical demands. By facilitating active, collaborative, and contextually relevant learning experiences, PBL might not only advance academic achievement but also could prepare students for the complexities of contemporary life and work.

2.1.2 Core Principles of PBL

PBL is a widely recognised educational model that seeks to promote an active and engaged learning experience by encouraging students to explore complex, real-world problems. This approach appears to prioritise the development of key skills for the modern era, such as problem-solving, collaboration, and adaptability. The core principles of PBL vary across different educational models. For instance, Barrows (1996) outlines six defining characteristics of PBL in McMaster and Maastricht Universities. Kolmos and De Graaff (2014)'s review outlined five key characteristics of PBL in Aalborg and Roskilde Universities, identified by Illeris (1974). A comprehensive understanding might be gained by examining the varying alignments. A critical review and comparison of these sources suggest a set of five core principles of PBL, as follows.

Student-Centric Learning and Independence: PBL emphasises student agency and independence. Learning is student-driven, with learners taking ownership of their educational journey by setting goals, making decisions, and managing projects. This principle fosters autonomy and self-regulation, enabling students to become active participants in their learning rather than passive recipients (Gao & Yang, 2023). By encouraging students to explore their curiosities, PBL nurtures a culture of inquiry and lifelong learning.

Collaboration and Social Learning: PBL often involves collaborative work, reflecting the real-world environments students will encounter professionally. This setting could facilitate the development of communication and interpersonal skills. Models of PBL emphasise teamwork, where students collectively engage in project tasks that require negotiation, delegation, and consensus-building (Simbolon, 2016). According to Kök and Duman (2023), students can learn from diverse perspectives and enhance their problem-solving capabilities through collaboration.

Inquiry-Based and Constructive Learning: PBL appears to centre on inquiry-based learning, where students investigate meaningful questions or challenges. This element could encourage critical thinking and creativity, as students must navigate complexities and uncertainties inherent in real-world problems. The investigative nature of PBL allows students to apply theoretical concepts to practical situations, thus deepening their understanding and retention of knowledge (Artama et al., 2023).

Authenticity and Real-World Connection: A notable principle across PBL models is the inclusion of authentic, real-world tasks that enhance the relevance and applicability of learning outcomes. When students work on projects with real-world significance, they might feel more engaged and motivated, recognising links between their academic work and societal needs (Kolmos & De Graaff, 2014). This real-world connection could aid in developing practical skills and preparing students for future career challenges.

Reflection and Metacognition: Within PBL, regular reflection is encouraged to assist students in understanding their learning processes. Reflective practices could offer opportunities for students to critically assess what they have learned, how they have learned, and what strategies might be improved. This continuous process of metacognition can support personal and academic growth, fostering higher-level thinking and adaptability (Saidova & Ergasheva, 2019).

Comparatively, different PBL models may place varying emphases on specific elements depending on the educational context and objectives. For instance, certain models might prioritise collaborative elements more heavily, while others might focus intensively on inquiry processes. Despite these variations, the most critical components of PBL, including student-centred learning, collaborative inquiry, real-world problem-solving, and reflective thinking, remain consistently highlighted as essential to effective project-based education.

The diverse approaches to PBL seem to share a common aim of integrating deep, engaged learning with real-world application. The core principles of PBL might not only support academic achievement but also provide students with transferable skills applicable to diverse contexts, potentially preparing them for life beyond the classroom. The adaptability and scalability of PBL suggest it could be a valuable instructional strategy across a range of educational settings, from primary schools to vocational training institutions.

2.1.3 Implementation Strategies for PBL

The implementation of PBL may benefit from careful strategic planning and an understanding of the various methodologies that can be applied across different educational contexts. A range of strategies have been explored for introducing and sustaining PBL in curricula, with some approaches potentially aligning pedagogical methods with institutional goals and the diverse learning needs of students.

One approach that has shown promise in PBL implementation involves using frameworks that emphasise real-world problem solving within flexible curricula. The xPBL methodology, for instance, has been designed for computing education by integrating real problems with professional oversight and artefact production. As discussed by Dos Santos et al. (2014), this method offers a structured yet adaptable approach to course design and includes management techniques aimed at balancing the demands of PBL with educational objectives, which may assist instructors in upholding academic standards.

Adapting PBL for fields such as management appears to benefit from involving both stakeholders and faculty in the planning process. This collaboration has been linked to aligning PBL models with course objectives and industry expectations, a notion supported by Huang and Zheng's (2011) exploration of PBL in Chinese universities' management curricula. Their work suggests that modifying PBL approaches to address cultural and curricular barriers can be an important step in tailoring these methods to specific educational environments.

In Hong Kong, the VTC, Hong Kong's largest vocational education provider, has adopted Gold Standard PBL to deliver industry-relevant training. Gold Standard PBL is a student-centred approach where learners address authentic, industry-aligned projects. The process involves identifying complex problems, generating hypotheses, conducting inquiry with industry resources, applying knowledge to develop solutions, and reflecting on outcomes (PBLWorks, 2019). Tutors facilitate small groups, promoting self-directed learning and hands-on application. This approach bridges classroom theory with workplace demands, as seen in initiatives like the VTC's 'Earn & Learn' Scheme.

Implementation strategies include crafting projects that reflect real-world challenges, leveraging industry partnerships for relevance, and using technology to enhance resource access (Vocational Training Council, 2020b). For instance, the Hong Kong Design Institute employs PBL in virtual production studios to train students in advanced media technologies. The VTC ensures inclusivity by tailoring PBL for diverse learners, such as non-Chinese speaking students, and aligns projects with the Hong Kong Qualifications Framework for quality assurance.

Furthermore, technological tools have been suggested to support PBL practices. For example, Learning Management Systems (LMS) and various digital resources may facilitate networked communication, ongoing assessment, and resource sharing - all important aspects of managing the multi-dimensional nature of PBL. Jin and Bridges (2014) indicate that integrating technological plug-ins with the PBL process can promote engagement and potentially enhance learning outcomes in health sciences education. However, the design and structure of an LMS might influence PBL delivery effectiveness. In a study by Ørngreen et al. (2021), Moodle was noted for focusing primarily on sharing information and teaching materials, which may not fully address the distinct needs of a PBL approach.

According to Yuan and Shen (2012), fostering students' autonomy and collaborative learning skills is a central element of implementing PBL. They suggest that courses should be designed to encourage both independent problem-solving and interpersonal collaboration, potentially equipping students to manage complex project dynamics. Their work also recommends that educators serve as facilitators rather than directors of learning, thereby helping students take a more active role in their educational journeys.

In addition, Miao et al. (2015) propose that a model-driven approach to PBL implementation can be useful for tailoring education experiences to the diverse needs of learners and subjects. By using PBL scripts and managing adaptations, educators might better align projects with specific learning outcomes, which could increase their relevance in various educational contexts.

Overall, effective PBL implementation appears to rely on a combination of strategic planning, stakeholder involvement, technological integration, and adaptability to specific educational contexts. While each strategy has its own potential advantages, collectively they contribute to creating an environment that emphasises student agency, engagement, and real-world application. Leveraging these strategies may help prepare students more effectively for future professional and academic challenges.

2.1.4 PBL in Vocational Education for Software Engineering

PBL is increasingly viewed as an important tool in vocational education, particularly in the field of software engineering. As the demands of the software industry evolve, many educational institutions are exploring PBL as one way to bridge the gap between theoretical knowledge and practical application, thereby potentially enhancing students' readiness for professional challenges.

PBL is thought to support the development of competencies required in software engineering by engaging students in real-world problem-solving scenarios. This pedagogical approach allows learners to apply theoretical concepts to practical tasks, which may contribute to improvements in problem-solving and independent learning skills. Towhidnejad and Aman (1996) suggest that integrating PBL into software engineering courses can foster these skills, possibly addressing some of the limitations observed in traditional instructional methods.

One example of aligning educational practices with industry needs through PBL is incorporating Agile methodologies, such as Scrum, into software engineering curricula. Scrum, a popular Agile framework, structures development into short iterative sprints, daily stand-ups, and key roles to enable adaptive planning, continuous feedback, and incremental software delivery. It has become mainstream in the software industry for handling evolving requirements, improving collaboration, and maintaining quality (Amazon Web Services, n.d.). Both Agile methodologies and PBL share similarities in their emphasis on iterative processes, collaborative teamwork, and adaptive problem-solving to address real-world challenges effectively. PBL may help develop skills, which are valued in the collaborative environments of information technology industry (El-Khalili, 2013).

Furthermore, PBL in vocational education appears to encourage self-directed learning, a quality considered important for success in software engineering. By engaging students in contextualised learning environments, PBL tends to promote greater autonomy and responsibility, traits frequently valued in technical professions (Zainol & Almukadi, 2020). Additionally, the experiential nature of PBL might enhance student motivation and retention, factors that can be critical in advanced learning contexts (Guedes et al., 2017).

The potential benefits of PBL in vocational education are also linked to its emphasis on collaboration between educational institutions and industry. Initiatives like cooperative education and commercial capstone projects may help ensure that graduates acquire skills that are relevant to today's job market (Reichlmay, 2006). Such alignment can contribute to better employability outcomes while also encouraging innovation and entrepreneurial thinking among students.

In summary, PBL in vocational education for software engineering appears to offer a multifaceted approach to skill development that aligns with evolving industry expectations. By integrating real-world problem-solving, Agile methods, and industry collaboration, PBL may help prepare students for the professional challenges ahead. The ongoing refinement of PBL models further suggests that this approach could play a significant role in developing a skilled and adaptable workforce.

2.1.5 Benefits of PBL in VPET and Software Engineering Study

PBL has gained attention as a potentially valuable approach in vocational education and software engineering. It seems to align well with the needs of today's workforce by offering students opportunities to apply theoretical knowledge in situations resembling real-world challenges. Incorporating PBL into curricula might help address some limitations of traditional education, especially in vocational training and computing fields.

One possible benefit of PBL in vocational education is its support for employability skills. It creates a hands-on learning environment where students can develop abilities like teamwork, communication, and problem-solving, skills that are often valued across industries. This could make PBL a helpful way to prepare students for the job market (Othman et al., 2017).

In software engineering education, PBL might help connect theory to practice by placing students in realistic scenarios that encourage self-directed learning and responsibility. Working through problem-based projects could teach students to manage tasks, meet deadlines, and collaborate effectively, which are the skills that tend to matter in software development and technical roles (Zainol & Almukadi, 2020). These competencies seem particularly relevant given how quickly the software engineering field evolves.

As stated in section 2.1.4, PBL might also tie in well with Agile methodologies. Industry's practices like Scrum, which focus on iterative progress and collaboration, appear to complement PBL's approach. Through this, students could gain practical experience, which might boost their readiness for professional roles (El-Khalili, 2013).

Beyond technical skills, PBL could encourage entrepreneurial thinking, especially in advanced software engineering settings. By guiding students through the process of designing and completing projects, it might foster creativity and a sense of ownership, qualities often linked to entrepreneurship (Guedes et al., 2017).

The flexibility of PBL in engineering fields suggests broader advantages as well. It could sharpen cognitive skills through challenging problem-solving tasks while creating an interactive, engaging classroom. By tackling realistic problems, students might deepen their grasp of theoretical ideas through practical application (Saleh et al., 2017).

PBL’s benefits might also reach beyond individual growth to strengthen ties between academia and industry. When educational projects reflect industry needs, institutions could better prepare students for real-world demands, potentially enriching the learning experience (Clyne & Billiar, 2016). This intersection of academia and industry might benefit both students and the wider educational ecosystem.

In conclusion, PBL seems to offer meaningful possibilities for vocational education and software engineering. By embracing this approach, institutions might provide students with an education that blends solid theory with practical relevance, helping them build the skills and confidence to succeed in a competitive, technologically-driven job market.

2.1.6 Challenges and Considerations in PBL in VPET and Software Engineering Study

PBL has attracted growing interest in vocational education and software engineering for its potential to connect educational goals with industry demands. However, putting PBL into practice in these areas comes with several challenges and considerations that educators might need to navigate to make it work effectively.

One key challenge could be blending traditional educational approaches with PBL’s more practical, flexible style. In software engineering, conventional teaching methods sometimes struggle to prepare students for real-world tasks, suggesting PBL could help by encouraging skills like independent learning and problem-solving (Brodie et al., 2008). The integration of Agile methodologies and industry-based scenarios might make PBL more relevant, though this could call for thoughtful curriculum planning and tailored assessment methods to meet learning objectives (El-Khalili, 2013).

Another aspect to consider is how well educational practices line up with industry expectations. Vocational education might benefit from PBL approaches that balance theory with hands-on experience to prepare students for the workforce. This blending can bring logistical hurdles, like building partnerships with industry players or adapting teaching methods to fit local needs (Yu et al., 2020). For example, rolling out PBL widely in vocational settings might stretch lecturers' abilities to find enough industry collaborators.

Assessment in PBL settings can also be tricky. Traditional tests might not fully capture the range of skills students pick up through hands-on projects, pointing to a need for custom evaluation tools that look at both the process and the end results to better gauge student progress (Kondo & Hazeyama, 2022). Time and resources are additional factors to think about, as PBL often demands more planning and coordination than standard courses. Educators might need to juggle the depth of PBL projects with the realities of tight schedules and limited materials (Hunt et al., 2010).

Student collaboration, a big part of PBL, brings its own set of dynamics. While working in groups can build teamwork and communication skills, it might also require careful guidance and strategies to handle disagreements, ensuring everyone gets something valuable out of it (Guedes et al., 2017).

Lastly, preparing faculty could be a vital piece of the puzzle. Teachers might need both teaching know-how and industry insights to steer students through real-world scenarios effectively. Ongoing training and ties with industry professionals could help link classroom learning to practical realities, potentially lifting the quality of vocational education (Matsuura, 2005).

In summary, while PBL offers promising possibilities for vocational education and software engineering, making it work well might involve thoughtful planning, creative assessment, industry connections, and support for educators. Tackling these points could help schools get the most out of this approach.

2.1.7 Integration with Self-Regulated Learning

PBL appears to create an environment that supports SRL, suggesting a potential connection between these two educational approaches. PBL seems to encourage students to take charge of their learning, which aligns well with SRL's focus on learners guiding their own education, including setting goals, tracking progress, and reflecting on results. The hands-on, engaging setup of PBL might give students room to explore and shape their learning paths, possibly fostering cognitive and metacognitive skills that tie into SRL. Some research points to PBL settings producing students who are better at problem-solving and critical thinking, which are the abilities often associated with self-regulation (Sahyar et al., 2017; Seo & Kim, 2013). By blending SRL practices into PBL, educators might create a space where students thrive academically while picking up habits that could serve them in lifelong learning. The next section will explore the literature on SRL, followed by a review that sheds light on how PBL and SRL might connect.

2.2 Self-Regulated Learning

SRL is often seen as an important idea in educational psychology, suggesting that learners can take an active part in their educational path. Unlike approaches where students rely mostly on outside direction, SRL tends to focus on independence, self-motivation, and a sense of ownership in learning. It appears to involve a repeating cycle where learners might set their own goals, track their progress, use strategies to address difficulties, and think about their experiences to improve down the line.

Models of SRL, like those put forward by Zimmerman and Bandura (1994), point to three main aspects: cognition, motivation, and metacognition. Cognition could mean applying learning strategies to make sense of new information. Motivation might involve the inner push to reach learning goals, possibly shaped by confidence in oneself and the kind of goals in mind. Metacognition seems to include planning, keeping an eye on progress, and reviewing one's efforts, which might help learners adapt their methods to fit different tasks or settings.

Recently, there has been noticeable interest in combining SRL with technology-supported learning environments and approaches like PBL. (Han, 2023; Lin & Chang, 2023; J. Jin & Bridges, 2014) These efforts might look to strengthen learners' abilities to guide themselves by offering tools and setups that encourage setting goals, learning purposefully, and reflecting on the process. As education moves towards putting learners more in charge, exploring and supporting SRL could turn out to be a valuable way to help students manage challenging learning situations and succeed academically.

2.2.1 Theoretical Foundations of SRL

The idea of SRL drew from various theoretical frameworks that collectively highlight autonomy, goal-setting, and strategic learning. Influential thinkers like Albert Bandura and Barry Zimmerman have shaped SRL as a multifaceted construct that integrates cognitive, motivational, and behavioural components. Bandura's social cognitive theory suggests that self-efficacy, beliefs in one's capabilities, is a core element driving self-regulation. Zimmerman built on this perspective by proposing a cyclical model, that includes stages of self-observation, self-judgment, and self-reaction as integral stages of self-regulation (Bozpolat, 2016).

Paul Pintrich's (1995) socio-cognitive model offers another angle, pointing to a possible interplay between learning strategies, motivation, and the settings in which learning happens. Pintrich's work leans towards the importance of learners' abilities to monitor and control their learning processes, suggesting that successful learners are those who can adapt their strategies based on feedback and reflection (Svinicki, 2010).

Phil Winne's model of SRL is a structured approach where learners take charge of their learning. It starts with task definition, where they understand what is required and assess available resources. Next, in goal setting and planning, they set specific goals and plan strategies to achieve them, breaking tasks into manageable parts. Then, during enactment, learners put plans into action, monitoring progress and adjusting as needed. Finally, in evaluation and adaptation, they reflect on their performance, deciding what worked and what to change for next time. This model shows learning as a flexible, ongoing process, with each phase building on the last (Winne & Hadwin, 1998).

Monique Boekaerts has enriched SRL by emphasising how motivation and emotions affect learning, going beyond just cognitive skills. Her work shows that successful learning involves managing feelings and staying motivated. She created the On-line Motivation Questionnaire to measure classroom motivation, helping educators support students better. Her research, detailed in publications like Boekaerts (1997) and Boekaerts and Corno (2005), connects emotions and motivation to how we learn, offering a broader view of SRL.

On the other hand, SRL can also be looked at through the lens of social and cultural contexts, as seen in Vygotsky's (1981) research. This view suggests that learning is inherently a social process. This perspective also suggests the necessity of scaffolding and co-regulation, where guidance from peers or teachers facilitates the development of self-regulatory skills (Bransen & Govaerts, 2020).

Together, these theoretical models offer a broad perspective on SRL, portraying learners as active participants who may adjust their strategies to meet personal learning goals. While not exhaustive, these models provide well-established frameworks grounded in research. For example, Pintrich's model combines cognitive strategies with motivation, Winne's model emphasises a feedback loop, and Boekaerts's model explores the connection between goal pursuit and emotional regulation. A study by Tinajero et al. (2024) suggests that Barry Zimmerman's cyclical model stands out as particularly influential in SRL research, noting its frequent citations and application across various educational settings. Given its prominence and the substantial body of work referencing it, Zimmerman's model offers a compelling focus for further exploration. This lays the groundwork for a deeper look at SRL components in the sections that follow.

2.2.2 Components of SRL

The components of SRL offer a way to look at how learners might manage and enrich their educational experiences. Barry Zimmerman's theory of SRL (2002) is often cited for its broad view, suggesting a mix of cognitive, metacognitive, and motivational pieces. According to the theory, these components work together to collectively enable learners to direct, monitor, and adapt their learning processes to achieve academic success.

Cognitive Components: At the core of SRL's cognitive aspects are the strategies learners use to acquire and organise information. These include techniques for effective note-taking, summarising, and elaborating on material, which help integrate new knowledge into existing cognitive structures. Zimmerman emphasises that these cognitive strategies are foundational to processing and retaining information, allowing learners to interact more dynamically with content (Bozpolat, 2016).

Metacognitive Components: Metacognition in SRL involves awareness and management of one's cognitive activities. It includes planning, monitoring, and evaluating one's understanding and performance. This reflective dimension allows learners to adjust their approaches based on feedback, making learning more effective and efficient. Through metacognition, learners can identify what they know, recognise areas that need improvement, and select strategies accordingly (Panadero & Alonso-Tapia, 2013).

Motivational Components: Motivation is a critical component of SRL, encompassing the beliefs and attitudes that affect learners' enthusiasms and persistence. Key motivational factors include self-efficacy, intrinsic motivation, and task value. These elements influence how learners perceive tasks and their ability to succeed, which in turn affects their engagement and perseverance. Zimmerman's model underscores the role of these motivational dimensions in sustaining effort and commitment throughout learning (Al-Alwan, 2008).

Taken together, these components sketch out a solid way to understand SRL. They reveal the interplay between internal and external factors in learning and highlight the active role students play in shaping their educational journeys. This understanding of SRL components might be useful for educators looking to encourage independence and adaptability in learners, possibly preparing them for diverse learning environments and challenges. As such, these insights could set the stage for exploring the specific phases of SRL, as detailed in subsequent discussions.

2.2.3 Phases of Self-Regulated Learning

The phases of SRL suggest a way to understand how learners might take charge of and enhance their educational experiences. Barry Zimmerman’s cyclical model offers a structured view that sheds light on how students could manage their learning. This framework points to three main phases: forethought, performance, and self-reflection. The cyclical model has been revised and evolved across time, and the latest version is by Zimmerman and Moylan (2009).

Forethought Phase: The forethought phase involves initial steps that could prepare learners for what is ahead. It might include analysing tasks and building self-motivation, like setting clear, doable goals and forming beliefs about their ability to succeed. This focus on planning ahead could help shape the strategies and actions that follow (Panadero & Alonso-Tapia, 2013).

Performance Phase: In the performance phase, learners might carry out activities that support their learning strategies. This could involve self-control such as staying focused and managing resources, and self-observation, where they keep track of how they are progressing towards their goals. This interplay might help them stay on path and adjust as things unfold (Bozpolat, 2016).

Self-Reflection Phase: The self-reflection phase encourages learners to look back at their efforts and results. It might include self-judgment and self-reaction, where they consider how well their strategies worked and whether they met their goals. This step could create a feedback loop, possibly influencing future planning and fine-tuning, which might support ongoing growth in learning (Panadero, 2017).

Zimmerman's model highlights a web of connected processes in SRL, suggesting that learning might not always move in a straight line but could cycle and adapt. This pattern might allow learners to polish their approaches over time, potentially strengthening their ability to learn independently. Exploring these phases could offer educators ideas for crafting teaching methods that encourage SRL, possibly nurturing both academic progress and skills for lifelong learning. These thoughts could lead into a discussion of specific ways to support SRL in education, as will be explored in subsequent sections.

2.2.4 Strategies for Promoting SRL

Promoting SRL might involve implementing strategies designed to enhance students' abilities to manage their own learning. This typically requires a multifaceted approach, potentially integrating cognitive, metacognitive, and motivational strategies to foster autonomy and active engagement in learning processes.

2.2.4.1 Cognitive and Metacognitive Strategies

One suggested strategy for promoting SRL is the development of effective cognitive and metacognitive skills. Educators may emphasise goal-setting, strategic planning, and self-monitoring techniques that enable students to regulate their learning activities. Techniques such as self-evaluation and reflective thinking may help learners assess their progress and adjust their strategies (Zimmerman et al., 1996).

2.2.4.2 Motivational Strategies

Motivation is often considered an important factor in SRL. Strategies that seek to build self-efficacy, enhance task value, and promote student ownership of learning are frequently viewed as useful for sustaining motivation (Weinstein et al., 2011). Educators might create learning environments that encourage student agency by offering choices and control over learning tasks, thereby potentially fostering intrinsic motivation.

2.2.4.3 Educational Environment and Teacher Support

A supportive educational environment can be beneficial for promoting SRL. Teachers appear to play a significant role, for instance, by modelling SRL strategies, providing constructive feedback, and creating a classroom climate that may encourage self-regulation (P. R. Pintrich, 1995). Additionally, structured classroom activities that incorporate SRL components might help students to practice and refine these skills (Russell et al., 2022).

2.2.4.4 Use of Technology and Innovative Tools

The integration of technology and innovative tools, such as online platforms, could support SRL by offering interactive and personalised learning experiences (Järvelä et al., 2015). These tools may encourage more SRL activities and provide opportunities for real-time feedback (Lim et al., 2022).

2.2.4.5 Lifelong Learning

Ultimately, one of the goals of promoting SRL is to prepare students for lifelong learning. Educators might aim to instil strategies that students could continue to use beyond the classroom, potentially fostering skills that may support their academic and professional endeavours throughout life (Candy, 1991).

Through the implementation of these strategies, educators may be able to promote SRL, thereby potentially empowering students to become more autonomous and motivated learners who can take charge of their educational trajectories. These principles provide a foundation for integrating SRL strategies into various educational contexts, which are explored in subsequent sections.

2.2.5 SRL in Educational Contexts

SRL is often regarded as a critical component of higher education, as it appears to enable students to take a more active role in managing their own learning processes. This capacity for self-management is considered by some to be important for academic success and lifelong learning, particularly in environments that demand independent and complex learning strategies.

In higher education, SRL is frequently recognised for its potential role in enhancing academic achievement and personal development. Some universities emphasise SRL as being important for fostering student independence and for preparing learners for the challenges of modern professional environments. Research has suggested that SRL may promote sustained knowledge building and adaptability in learning contexts, factors that could be relevant for success in higher education and beyond (P. R. Pintrich, 1995).

Educators are generally seen as playing a pivotal role in cultivating SRL competencies among students. Teaching strategies that place an emphasis on goal setting, self-monitoring, and reflection are thought to be instrumental in the development of self-regulatory skills. Faculty may support SRL by modelling appropriate strategies, providing constructive feedback, and creating classroom environments that encourage self-reflection and independent learning (Russell et al., 2022). Such interventions could help students to incorporate SRL practices into their academic routines, thereby potentially enhancing both their motivation and academic performance.

Despite the reported benefits of SRL, its integration into higher education can present certain challenges. Interventions aimed at fostering SRL may be complex, as they might require not only adjustments to curricula but also broader shifts in institutional culture and student attitudes. Moreover, the outcomes of these interventions could be moderated by factors such as student motivation, and the specific educational context (Jansen et al., 2019).

In conclusion, SRL is often considered a cornerstone for helping students manage their own learning in higher education. By fostering environments that support SRL, institutions may not only enhance academic outcomes but also equip students with skills that could contribute to ongoing personal and professional growth. These foundational insights into SRL in higher education provide a basis for exploring its specific applications within software engineering education in subsequent sections.

2.2.6 SRL in Software Engineering Education

SRL is increasingly regarded as an important component within software engineering education, as it could potentially provide students with critical skills that support both academic and professional success. This educational approach appears to encourage learners to take greater control of their own learning processes, possibly fostering independence and adaptability in rapidly changing technological landscapes.

2.2.6.1 Integration with PBL

In several studies, PBL is seen as a method that aligns well with SRL principles in the software engineering context (Guedes et al., 2017; Yu et al., 2020). Through PBL, students may engage in real-world software development projects that require them to plan, execute, and assess their efforts autonomously. This hands-on approach is thought to not only help enhance technical skills but also to support the development of self-regulatory abilities such as goal setting, progress monitoring, and reflective evaluation of performance.

2.2.6.2 Technological Tools and Blended Learning

The use of technological tools, including blended learning models and integrated development environments (IDEs), is frequently suggested as playing a significant role in promoting SRL within software engineering education. For example, IDEs are sometimes viewed as useful for supporting SRL by providing students with real-time feedback on their coding practices, thus fostering a self-guided learning process (Ding, 2014). On the other hand, blended learning, which combines traditional classroom instruction with online resources, may allow students to tailor their learning experiences to their individual needs (Milligan et al., 2016).

2.2.6.3 Reflective Practice and Learning Analytics

Reflective practice is another component of SRL that is often integrated into software engineering curricula. This practice can enable students to critically evaluate their work and might enhance their understanding of both the subject matter and their personal learning strategies (C. N. Bull & Whittle, 2014). In addition, learning analytics could provide valuable insights into students' learning behaviours, allowing educators to design learning environments that further support self-regulation by addressing individual learner needs (Pratheesh & Devi, 2016).

In summary, the integration of SRL in software engineering education appears to offer the potential to enrich students' academic experiences and to better prepare them for workforce demands, where self-direction and continuous learning are highly valued. As the field continues to evolve, further research into effective assessment methods for SRL might be necessary to ensure that learners can reliably monitor and evaluate their development. Such ongoing assessment is likely to be crucial for refining pedagogical strategies and enhancing learning outcomes in software engineering education.

2.2.7 Assessment of SRL

Assessing SRL competencies in students requires a comprehensive approach that captures both measurable outcomes and nuanced insights into learning processes. This can be achieved through a combination of quantitative and qualitative methodologies, each offering distinct perspectives on how students set goals, monitor their learning, and regulate their study habits.

Quantitatively, tools like the Motivated Strategies for Learning Questionnaire (MSLQ), developed by Pintrich and De Groot (1990), are widely used to evaluate dimensions of student motivation and learning strategies, including goal orientation, self-efficacy, and metacognitive strategies (P. R. Pintrich et al., 1993). Qualitatively, methods such as interviews, observational studies, and reflective journals provide deeper insights into students' personal experiences, socio-emotional aspects of learning, and real-time application of SRL strategies (Creswell & Creswell, 2018; Patton, 2015; Schön, 1987).

An integrative approach, such as the Sequential Exploratory Design (SED), combines qualitative exploration with quantitative measurement to ensure a holistic understanding of SRL. This mixed-methods strategy allows for the grounding of quantitative tools like the MSLQ in real student experiences identified through initial qualitative data (Yin, 2017). While this section provides an overview of SRL assessment approaches, a detailed discussion of the specific methods, design, data collection, and analysis employed in this study is presented in Chapter 3, Section 3.1.2 (Research Methodology).

2.2.8 Role of Technology in Supporting SRL

The integration of technology into educational practices appears to offer potential benefits for enhancing SRL by providing tools and environments that support the autonomous regulation of learning processes. Technological advancements may introduce innovative platforms and resources that help students develop and refine SRL skills, potentially making education more personalised and effective.

2.2.8.1 Enhancing SRL through Technology

Technology may support SRL by enabling individualised learning experiences in which students can manage the pacing, timing, and location of their studies. This flexibility might foster a sense of responsibility and control, allowing learners to tailor their educational journey according to personal goals and needs (Nat et al., 2011). Moreover, digital platforms could enhance student autonomy and engagement by offering interactive and customisable environments that encourage self-assessment and reflection (Chelghoum, 2017).

2.2.8.2 Tools and Platforms for SRL Process

Tools such as learning management systems (e.g., Moodle) and interactive applications (e.g., Padlet, Kahoot) are often assumed to provide structures for monitoring and assessing student progress. These platforms may promote self-regulation through visual feedback and gamified learning scenarios (Alhalafawy & Tawfiq Zaki, 2022). In addition, such technologies might facilitate the development of metacognitive strategies that are considered essential for effective SRL, thereby helping students to gain a better understanding of their learning processes and outcomes.

2.2.8.3 The Role of Feedback and Analytics

Technology may not only aid in providing consistent and immediate feedback but also leverage learning analytics to offer detailed insights into students' learning behaviours. These data might inform tailored support and interventions by identifying areas of strength and areas in need of improvement (Budiharjo, 2017). This continuous feedback loop could help learners adjust their strategies and improve self-regulation systematically.

2.2.8.4 Technological Challenges and Considerations

Despite the potential benefits, integrating technology into SRL may present certain challenges. Ensuring that technological tools effectively support rather than hinder the learning process likely requires careful design and implementation. It appears important that educators develop proficiency in incorporating these tools into curricula in ways that genuinely enhance student autonomy and engagement without overwhelming learners (Nussbaumer et al., 2011).

Overall, the role of technology in supporting SRL seems to be both potentially transformative and complex. By leveraging digital tools and platforms, educators may be able to create enriched learning environments that encourage SRL, thereby better preparing students for the demands of continuous learning and adaptation in diverse vocational and academic contexts. These insights help inform the implications for vocational education, which are discussed further in the next section.

2.2.9 Implications for Vocational Education

The integration and promotion of SRL is increasingly seen as a potentially valuable component in vocational education. It may help equip students with the autonomy and skills that appear to be needed for success in dynamic professional environments. Incorporating SRL into vocational curricula might assist in preparing students to navigate career challenges and potentially embrace lifelong learning.

2.2.9.1 Importance of SRL in Vocational Education

SRL is frequently credited with empowering vocational students to take a more active role in managing their own learning. By fostering skills such as self-monitoring, strategic planning, and reflective thinking, SRL may contribute to the development of the adaptability and independence that some vocational fields appear to require—especially in contexts where practical, real-world applications and hands-on experiences predominate (Mejeh & Held, 2022). Some educators in vocational settings are encouraged to design curricula that integrate SRL strategies, which could help students create effective work environments and manage their emotional and motivational states (Van Grinsven & Tillema, 2006).

2.2.9.2 Strategies for Enhancing SRL

Promoting SRL in vocational education often involves the implementation of strategies aligned with students' professional aspirations and practical skill development. Techniques such as learning contracts, reflective practice, and goal-oriented tasks have been suggested as potentially effective. These strategies may encourage learners to set personal learning objectives and actively engage with their educational experiences, thereby possibly enhancing both self-awareness and professional competency (Tsang et al., 2002).

2.2.9.3 Challenges and Opportunities

While the benefits of SRL have been noted in various studies, its promotion in vocational education also presents several challenges. For instance, addressing the diverse needs of learners and fostering a supportive learning environment may prove complex. Instructors are often expected to be adept at motivating students and facilitating the development of SRL skills, especially where learners display varied educational backgrounds and differing levels of motivation (Russell et al., 2022).

2.2.9.4 Implications for Professional Development

Incorporating SRL within vocational education may have implications for both student learning and teacher professional development. Educators are sometimes advised to model self-regulation and provide constructive feedback that supports students' abilities to manage their learning. Additionally, some vocational training programmes might benefit from integrating SRL into teacher training, which could help ensure that educators are well-equipped to promote these skills effectively (Jossberger et al., 2010).

Overall, the integration of SRL in vocational education appears likely to enhance students' capacities to learn independently and adapt to changing workplace demands. As such, SRL is increasingly viewed as a potentially crucial framework for vocational training, supporting the development of learners who may be better prepared for the complexities of modern careers. These foundational insights provide a basis for exploring the integration of SRL with Conversational AI and PBL, which is discussed in the following section.

2.2.10 Integration of Conversational AI in PBL and SRL

In modern education, integrating PBL with SRL appears to present a unique opportunity to foster independent, reflective, and engaged learners. PBL's focus on real-world applications and student ownership of projects (Gligorea et al., 2023) tends to complement SRL's emphasis on autonomous learning processes, where students are encouraged to set their own goals, monitor their progress, and reflect on their outcomes (Zimmerman, 2002). However, realising the full potential of PBL in cultivating SRL may require innovative tools that offer timely feedback and personalised support throughout the learning journey.

AI tools, particularly those driven by LLMs such as ChatGPT, have emerged as promising allies in this educational paradigm. These AI systems utilise advanced natural language processing capabilities to deliver real-time, interactive support that may enhance SRL within PBL environments. By providing instant feedback, Conversational AI can reduce the time lag between student inquiry and response, thereby supporting an environment of continuous learning and adaptation. This immediate interaction encourages learners to make more informed decisions about their learning paths, which is considered crucial for effective SRL (Fryer et al. 2020; Huang et al. 2024).

Conversational AI is also capable of tailoring interactions to accommodate varying learning paces, which can be beneficial for students with diverse needs in PBL. Such personalisation is integral to SRL, as it empowers students to manage their learning processes more effectively by adjusting their strategies in response to AI-provided insights. The capacity of AI to scaffold learning through adaptive recommendations aligns with the core principles of SRL, potentially enhancing both motivation and engagement by making learning experiences more relevant and targeted (Kulkarni et al., 2019).

In addition to supporting individual learning, Conversational AI has the potential to facilitate the collaborative aspects of PBL. By acting as a mediator in group projects, AI tools can help manage communication and task allocation, ensuring that all members are actively contributing and reflecting on their roles within the team. This organisational support may enhance overall group SRL, encouraging students to collectively and individually reflect on both their achievements and challenges (Ji et al., 2023; Wan & Hu, 2022).

Furthermore, the flexible nature of Conversational AI makes it an invaluable resource for educators, relieving some of the resource constraints often associated with PBL. By providing round-the-clock support and handling routine inquiries, AI can enable educators to concentrate more on developing high-quality, project-based curricula and promoting deeper student engagement. This shift may lead to a more effective utilisation of both human and technological resources, optimising learning outcomes across diverse educational contexts (Adiguzel et al., 2023).

In summary, the integration of Conversational AI into PBL settings holds substantial promise for enhancing SRL among students. By offering personalised, immediate, and adaptive support, these AI tools address key challenges in PBL, paving the way for more engaging, efficient, and autonomous learning experiences. As educational institutions increasingly adopt AI technologies, the potential to enrich both teaching and learning environments becomes ever more apparent, setting the stage for the next exploration into how Conversational AI can be systematically harnessed in educational settings.

2.3 Conversational AI in Education

The section on Conversational AI in Education explores the intersection of artificial intelligence, natural language processing, and educational practices. The literature review examines how Conversational AI technologies have been developed and integrated into educational settings, their theoretical underpinnings, applications, benefits, and challenges. Specifically, it also considers the potential of Conversational AI to support learning processes such as self-regulation and project-based learning, with a focus on software engineering education in vocational contexts.

2.3.1 Conversational AI Technologies in Education

Conversational AI technologies, including chatbots and LLMs like ChatGPT, have been increasingly integrated into educational settings, potentially offering innovative approaches to enhance teaching and learning experiences. These technologies often utilise natural language processing (NLP) to facilitate interactions between learners and digital platforms, which may provide personalised and scalable educational support.

2.3.1.1 Chatbots in Education

Chatbots are interactive platforms that utilise AI to simulate conversation with users. In educational contexts, they have been deployed as virtual tutors and assistants, helping students access information, practice language skills, and potentially receive immediate feedback on their queries (Bhujbal et al., 2022; Hakim & Rima, 2022). Such bots might manage frequently asked questions, support learners in navigating course content, and engage students in interactive learning activities, thereby possibly enhancing access to educational resources.

2.3.1.2 LLMs and ChatGPT

Large language models have contributed to the evolving landscape of Conversational AI by offering more sophisticated language understanding and generation. ChatGPT, one of the market leading LLM evaluated by rigorous benchmarks, shows its capacity in factual accuracy, reasoning, natural language process tasks, instruction following, and give human-like response. (OpenAI, 2024) ChatGPT has been used to provide tailored educational experiences by adapting to individual learning preferences. For example, it has been implemented as a platform for English language learning and other academic subjects, potentially facilitating personalised interactions and dynamic feedback (Park, 2023). Despite the benefits, challenges such as ensuring content accuracy and navigating ethical considerations remain prevalent (Shaw et al., 2023).

2.3.1.3 AI Integration with PBL

The incorporation of AI and chatbots into PBL frameworks has been highlighted for its potential to support self-directed learning by guiding students through complex projects. This approach may foster student autonomy while also encouraging the development of critical thinking and problem-solving skills (Wan & Hu, 2022). AI-driven conversational tools can thus be viewed as potential facilitators of PBL, offering scaffolding and adaptive feedback that might adjust according to student performance.

Overall, Conversational AI technologies suggest a possible shift towards more interactive and responsive educational systems. By capitalising on the adaptive capabilities of AI, these technologies may offer opportunities to personalise education and address individual learning needs more effectively. This literature review thus sets the stage for a closer examination of the specific applications of Conversational AI in educational settings.

2.3.2 Applications of Conversational AI in Educational Settings

Conversational AI technologies, including chatbots and advanced language models such as ChatGPT, have been increasingly deployed across a range of educational settings (Huang et al. 2024) with the potential to enhance learning experiences and teaching methodologies. These technologies utilise sophisticated natural language processing techniques to help create more personalised and interactive educational environments.

2.3.2.1 Enhancing Language Education

Conversational AI has been suggested to be promising for language education, as it is found that Conversational AI could offer students personalised opportunities to practice and improve their language skills (Ji et al., 2023). By engaging with AI-driven chatbots, students might participate in real-time conversations that have the potential to enhance their spoken and written language abilities. These AI tools could provide instant feedback and corrections, which in turn may support language acquisition and enable learners to practice beyond traditional classroom settings (Ji et al., 2023).

2.3.2.2 Supporting Self-Paced and Autonomous Learning

Conversational agents have been integrated into certain educational platforms to support self-paced and autonomous learning. By offering guidance and resources on demand, chatbots may encourage learners to explore content at their own pace, potentially enhancing comprehension and retention. This capability appears to be particularly beneficial in subjects such as chemistry, where AI chatbots have been utilised to support the development of self-study skills by providing tailored assistance and additional learning materials (Giam et al., 2023).

2.3.2.3 Curriculum Enhancement and Engagement

The application of Conversational AI appears to extend beyond individual learning support to broader curricular integration. Through AI-driven interactions, students might explore complex topics in more engaging ways, which could enhance their overall educational experience. For instance, some studies have utilised AI to simulate real-world scenarios, contributing to improved curriculum delivery and more accessible student interactions (Song et al., 2023).

2.3.2.4 Addressing Educational Challenges

While Conversational AI may offer benefits in enhancing educational delivery, it is not without challenges. Issues such as ensuring data privacy, managing the ethical use of AI, and maintaining high-quality educational content remain important concerns. Efforts to develop AI systems that address a diverse range of learning needs and contexts continue to be a significant focus for educational technologists (Adiguzel et al., 2023).

In summary, Conversational AI technologies appear to be contributing to a transformation of educational landscapes by offering dynamic and interactive learning experiences. Their ability to adapt to individual learner needs, support engagement, and facilitate autonomous learning suggests potential for comprehensive educational enhancement. As these technologies continue to evolve, further research and development may better inform their integration into more complex educational settings, such as PBL, which is discussed in the following section.

2.3.3 Conversational AI in Project-Based Learning

The application of Conversational AI within PBL contexts may present a dynamic approach to education that leverages technology to foster interactive and responsive learning environments. Conversational AI tools, such as chatbots and intelligent agents, have increasingly been integrated into PBL frameworks to support student engagement, facilitate exploration, and enhance collaborative learning outcomes (Ji et al., 2023; Lin & Chang, 2023).

2.3.3.1 Enhancements in Engagement and Exploration

Conversational AI might play a pivotal role in enhancing student engagement by providing real-time interactive support and facilitating exploration within PBL activities. By employing AI-driven conversational interfaces such as chatbots, students may be able to access immediate feedback and guidance, which could help sustain motivation and potentially encourage deeper engagement with project content (Song et al., 2023). This continuous interaction is likely to support learners in managing complex tasks, thereby allowing them to explore subject matter with increased confidence and autonomy.

2.3.3.2 Facilitating Collaborative Learning

AI conversational agents appear to be particularly promising in PBL settings for fostering collaborative learning. For instance, tools such as MentorChat have been reported to support academically productive discussion among students, which may enable them to engage in meaningful dialogue and potentially improve their problem-solving skills (Tegos et al., 2014). These AI systems may facilitate communication and collaboration by guiding discussions and helping students articulate their thoughts more coherently, thereby contributing to enhanced educational outcomes.

2.3.3.3 Adaptive and Personalised Learning

The adaptability of Conversational AI may enable more personalised learning experiences within PBL projects. AI systems can sometimes tailor interactions to meet individual student needs, adopting conversational strategies to foster better understanding and skill acquisition (Chhibber & Law, 2021). This personalisation appears to support SRL by encouraging students to take ownership of their educational journeys and develop skills aligned with their personal learning goals.

2.3.3.4 Innovative Educational Practices

The integration of Conversational AI in PBL has been reported to introduce innovative educational practices that blend AI capabilities with more traditional pedagogies. For example, using Conversational AI to simulate real-world scenarios within project tasks may help bridge the gap between theoretical knowledge and practical application, potentially making learning more relevant and engaging for students (Wan & Hu, 2022).

In conclusion, Conversational AI in PBL may offer significant potential to enhance educational experiences by promoting engagement, facilitating collaboration, and supporting personalised learning. As these technologies continue to evolve, they may further enrich educational methodologies and outcomes, particularly in disciplines such as software engineering education, which is discussed in the following section.

2.3.4 Benefits for Software Engineering Education

Conversational AI, particularly through tools like ChatGPT, appears to be significantly impacting software engineering education by influencing both teaching methodologies and student learning experiences. These AI-driven platforms provide potential benefits such as personalised feedback, interactive engagement, and the development of critical programming skills.

2.3.4.1 Personalised Feedback and Learning Paths

One of the primary benefits reported from integrating Conversational AI in software engineering education is its potential to deliver personalised feedback and to tailor learning experiences to individual student needs. AI platforms may offer contextualised explanations and immediate support, thereby helping students to understand complex coding concepts and to engage in hands-on practice (Bull & Kharrufa 2024). Such personalised interaction not only appears to aid comprehension but may also allow for adaptive learning paths that reinforce understanding through iterative processes (Qadir, 2023).

2.3.4.2 Enhancing Programming Literacy

Conversational AI is also seen as playing a role in developing programming literacy by facilitating more effective communication between students and technology. This interaction can help learners to build their programming language proficiency – a skill that is vital in both academic and professional software engineering contexts (Chilana et al., 2016). Moreover, the capacity to converse with AI systems may enhance students' confidence and potentially improve their marketability by bridging the gap between theoretical knowledge and practical application.

2.3.4.3 Facilitation of Realistic Simulations and Coding Exercises

AI tools like ChatGPT appear to enable realistic virtual simulations and coding exercises, offering students a practical and application-oriented learning experience. Such exercises have been reported to reinforce the theoretical principles taught in software engineering courses, helping students to better grasp the requirements and intricacies of software development (Abdelfattah et al., 2023).

2.3.4.4 Increased Engagement and Motivation

By incorporating Conversational AI, educators may transform traditional learning environments into more interactive settings, which can lead to increased student engagement and motivation. The dynamic nature of AI interactions seems to encourage active participation and foster a more productive educational atmosphere (Allam et al., 2023).

Overall, the integration of Conversational AI in software engineering education appears to offer substantial benefits, including personalised learning experiences, enhanced engagement, and improved programming skills. These advantages underscore the potential for AI technologies to enrich educational experiences and outcomes. This discussion sets the stage for exploring the challenges and considerations associated with implementing Conversational AI, which are addressed in the following section.

2.3.5 Challenges and Considerations

The use of Conversational AI in educational settings brings up a variety of challenges and considerations that educators and developers need to think about to make the most of these tools whilst at the same time keeping potential downsides in check. These issues seem to span technical, ethical, and teaching-related areas, suggesting a layered set of hurdles to navigate.

2.3.5.1 Integration and Collaboration Challenges

One possible challenge in integrating Conversational AI into education could be figuring out how it works alongside human teachers. AI might help by taking on routine tasks or offering tailored support, but there is not much solid evidence yet on how well it teams up with educators, pointing to a gap worth exploring (Ji et al., 2023). It is suggested that enabling a smooth fit might call for some careful planning and tweaks to teaching approaches to make room for AI-assisted moments (Jadeja & Varia, 2017).

2.3.5.2 Ethical and Privacy Concerns

The use of Conversational AI in education could raise ethical issues related to data privacy and the potential for bias. AI systems often learn from large datasets, which might embed and amplify biases present in their training data, leading to discriminatory outputs that perpetuate stereotypes in educational content, assessments, or recommendations, disproportionately affecting marginalised groups and undermining equitable learning environments (Charles, 2024; Pham et al., 2024; Wargo & Anderson, 2024). On top of that, keeping the privacy and security of student data is a big concern, needing strict compliance with data protection standards (Ruane et al., 2019). There is also potential for creating new forms of inequity such as widening the digital divide where students from under-resourced backgrounds lack access to reliable or enhanced AI tools or high-speed internet, thus disadvantaging them relative to more privileged peers and exacerbating existing socioeconomic disparities in learning opportunities (Charles, 2024; Pham et al., 2024; Wargo & Anderson, 2024).

2.3.5.3 Emotional and Socio-Cultural Challenges

Conversational AI's limitations in emotional intelligence, often referred to as the "empathy gap", could present challenges in adequately addressing students' emotional needs, particularly in younger or emotionally vulnerable learners. These limitations could affect student engagement and learning outcomes, suggesting a need for responsible and empathetic AI design (Kurian, 2023).

2.3.5.4 Technical and Educational Implementation

From a technical perspective, developing Conversational AI that effectively simulates human interaction and adapts to diverse educational contexts presents significant challenges. This includes defining clear success metrics and ensuring that AI systems can handle the intricacies of real-time educational engagement without creating dependency or hindering traditional learning processes (Adiguzel et al., 2023). Additionally, ongoing teacher training and professional development are crucial to equip educators with the skills necessary to integrate and leverage AI technologies effectively (Tafazoli, 2024).

2.3.6 Conversational AI towards PBL and SRL

Conversational AI seems to offer interesting possibilities for shaping educational settings, though making the most of it might involve carefully tackling the challenges and considerations that are clear. By paying attention to ethical use, thoughtful integration, and ongoing support for educators, the education field could tap into what AI tools might bring to teaching and learning, potentially creating a safer and fairer experience for learners. This approach paves the way for exploring what it means for software engineering education, as covered in the next section.

2.4 Relationship Between PBL, SRL and Conversational AI

PBL is an educational approach where students engage with real-world problems, often collaboratively, to develop skills such as critical thinking and teamwork. SRL refers to students taking an active role in managing their learning process, including setting goals and reflecting on their progress. Research, such as that by Kang and Kim (2002), suggests that the structured nature of PBL may support the development of SRL by encouraging students to plan, implement, and assess their projects. This process could foster self-regulatory skills, such as time management, though further evidence might strengthen this connection.

PBL may promote learner autonomy, a key aspect of SRL, by giving students opportunities to direct their learning through personalised project design. This approach could enhance engagement and a sense of ownership, as students tailor projects to their interests and learning goals. Studies like those of Rostom (2019) and Villaflor and Zhang suggest this alignment may create motivation and self-awareness, though the extent of these effects could vary depending on context and implementation.

Conversational AI has emerged as a tool with the potential to enhance the integration of PBL and SRL. By offering interactive and adaptive feedback, AI-driven conversational agents might support the development of self-regulation skills in real-time. These agents could serve as “virtual tutors”, providing tailored guidance and encouragement, which may be especially useful in PBL settings where students tackle complex, open-ended tasks. Kowald and Bruns (2019) suggest this personalised support could be beneficial, though more research might clarify its impact.

The use of Conversational AI in PBL settings could facilitate reflection and critical thinking through dialogue-based interactions. AI tools might guide students through project phases by prompting them to explore different problem-solving strategies and reflect on their experiences, potentially enhancing metacognitive awareness. Lin and Chang (2023) indicate this guidance may play a role in supporting such outcomes, though the effectiveness likely depends on how the AI is implemented.

Integrating Conversational AI into PBL might broaden educational opportunities by offering scalable support that adapts to varying classroom dynamics. AI systems could complement traditional learning approaches by providing additional resources and interaction, potentially improving both individual and collaborative experiences. Research (Hoai Nam & Giang, 2023) suggests this augmentation may elevate learning outcomes, though its success could hinge on factors like technology access and teacher facilitation.

In summary, combining Conversational AI with PBL and SRL may create an educational environment that fosters deeper engagement, personalises learning, and supports the development of essential lifelong learning skills. As educational contexts evolve, exploring these synergies could be valuable in preparing students for modern challenges. This discussion provides a foundation for examining their application in software engineering education, which is addressed in the next section.

2.5 Theoretical Framework for the Study

To develop a theoretical framework for a study exploring PBL enhanced by Conversational AI and its impact on student performance through SRL using Zimmerman’s model, several educational theories and concepts can be brought together. Following is an outline of how these ideas might connect.

2.5.1 Key Elements of the Theoretical Framework

The PBL framework is grounded in constructivist learning principles, which view learning as an active and student-driven process. In PBL, students engage with complex, real-world projects that challenge them to develop essential skills such as problem-solving, critical thinking, and teamwork. By working on authentic tasks, students are encouraged to explore and apply theoretical concepts in practical contexts, making their learning experience more relevant and meaningful. Collaborative learning is a cornerstone of PBL, where students work together, exchange ideas, and construct knowledge as a group, fostering a dynamic environment that bridges theory and application through shared perspectives.

SRL, as articulated in Zimmerman's model, provides a structured approach to how students manage their learning within the PBL framework. The model consists of three phases: the forethought phase, where students set goals and plan their strategies, identifying the resources and approaches they will need for a project; the performance phase, where they employ self-control and self-observation to monitor their progress and stay on track; and the self-reflection phase, where they evaluate their performance and learning outcomes, using these insights to inform future efforts. This cyclical process empowers students to take ownership of their learning, enhancing their ability to navigate the challenges of PBL effectively.

Conversational AI serves as a powerful learning enhancer, complementing both PBL and SRL by providing tailored support to students. It offers immediate feedback and real-time guidance, enabling students to make adjustments as they work through tasks. Additionally, conversational AI acts as a scaffolding tool by breaking down complex tasks, clarifying concepts, and delivering personalised resources that align with individual needs. By adapting its responses to a student's interaction style or learning pace, the AI creates adaptive learning paths that cater to diverse preferences, fostering a more personalised and effective learning experience within the PBL and SRL frameworks.

2.5.2 Integration of Theories

This framework suggests that blending Conversational AI with PBL could support the SRL process outlined by Zimmerman. The AI might play a role in each phase:

In the *Forethought Phase*, it could help students set practical goals and map out their project plans.

During the *Performance Phase*, it might offer feedback and assist with self-monitoring, helping students stay aligned with their goals, which can potentially act as a virtual teammate, teaching assistant, or even an industry perspective.

In the *Self-Reflection Phase*, it could prompt students to think about their results and process, encouraging them to gain insights into their learning strategies.

By combining these elements together, the framework seeks to explore how students manage their learning and perform in PBL settings when supported by Conversational AI. Zimmerman's SRL model offers a structured way to identify, facilitate and measure this, shedding light on how these tools might influence students' abilities to regulate their learning and enhance their overall outcomes.

2.6 Research Gaps and Needs

Drawing from the current literature, several potential gaps and areas for further exploration emerge when considering the role of Conversational AI in fostering SRL within PBL environments, particularly for software engineering students in vocational education.

2.6.1 Research Gaps

2.6.1.1 Integration of Conversational AI with PBL and SRL

While there is substantial work on Conversational AI in education, as well as on PBL and SRL separately, how these elements come together, specifically how Conversational AI might enhance SRL within PBL, seems underexplored. It appears no study dives deeply into the ways AI tools could support learners' self-regulatory processes in a project-based setting, though there are studies that explore the use of SRL or PBL respectively.

There are eight recent studies identified that explore how novel conversational AI supports students' SRL. The studies explore the potential of AI to support

SRL in online and digital environments. Studies have investigated AI applications for measuring and enhancing SRL processes (S.-H. Jin et al., 2023; Lim et al., 2023; C.-Y. Wang & Lin, 2023), including the utilisation of chatbots and LLMs (Lai, 2024; Ng, Tan, et al., 2024). Researchers have proposed hybrid human-AI regulation systems to gradually transfer control from AI to learners (Molenaar, 2022) and examined the effects of personalised AI-based scaffolds on SRL activities (Lim et al., 2023). The integration of explainable AI and open learner models has been suggested to empower learners in AI-supported SRL (Kay, 2023). Whilst AI demonstrates potential in enhancing students' science knowledge, motivation, and SRL skills (Ng et al. 2024), challenges persist in accurately measuring SRL processes using multimodal data streams (Lim et al., 2023).

On the other hand, there are 10 recent research studies identified related to AI in PBL, presenting the integration of AI in PBL across various educational contexts. Studies have investigated co-designing AI usage with students (Zheng et al., 2024), developing AI literacy frameworks (T. Wu & Chang, 2023), and facilitating PBL utilising AI (Bi, 2024; Dinger et al., 2024; Kimmel, 2024; Ito et al., 2021). Researchers have examined AI's potential to enhance critical thinking skills, improve student engagement and achieve sustainability goals in various disciplines by solving real-world problems. The integration of ChatGPT in PBL has been systematically reviewed (Purnama et al., 2023), which identified PBL can enhance personalised, interactive education, fostering student engagement, critical thinking, and collaborative problem-solving. Another study has focused on using platforms such as Minecraft for AI PBL (Singh, 2020). Additionally, Ng et al. (2024) conducted a comprehensive review of AI literacy education in secondary schools on pedagogical approaches, teaching tools and assessment methods.

Though there are studies showing AI in PBL can enhance students' skills related to SRL like critical thinking, there is no study directly exploring the effect of the use of AI in PBL on students' SRL.

2.6.1.2 Contextual Focus on Vocational Education

The application of AI, including conversational AI tools such as ChatGPT, has gained attention in VPET for its potential to enhance teaching and learning processes. A review of approximately 14 studies indicates that AI supports vocational education through improved teaching efficiency, personalised learning experiences, and better alignment of curricula with labour market needs (Rosyadi et al., 2023). Notable AI applications include adaptive learning systems, virtual simulations, intelligent tutoring, and career guidance tools, which contribute to skills development and innovation (Amdan et al., 2024; Duan & Suhan, 2024; L. Wang, 2024). Additionally, AI facilitates employability by analysing labour market trends to inform curriculum design (S. Wu & Luo, 2024). The literature also highlights challenges such as digital inequality, the need for educator training, and ethical issues, including data privacy and algorithmic bias (Ejjami, 2024). To address these, researchers suggest investments in infrastructure, professional development, and specialised roles to support equitable AI implementation (Ghosh & Ravichandran, 2024).

Whilst the existing literature offers valuable insights into AI applications in VPET, there is limited exploration of its role in supporting students' SRL and its potential contributions to PBL environments. Few studies have examined how conversational AI might assist vocational students in developing skills such as metacognition, goal-setting, or self-monitoring, which are integral to SRL. Similarly, there is a lack of research on how AI could enhance collaborative and enquiry-based learning in PBL settings, which are often emphasised in vocational education for their focus on practical skills development. This gap suggests a need for further research to explore the potential of conversational AI in fostering SRL and supporting PBL in vocational contexts, considering PBL is one of the major pedagogies adopted by the Hong Kong VPET environment (Vocational Training Council, 2020b).

2.6.1.3 Outcome Specific to Software Engineering Students

There are studies exploring the impact of Conversational AI in educational context. However, studies on Conversational AI in conjunction with pedagogical theories like PBL and SRL for software engineering students appear limited. Three related studies were identified. Two of them explore effective teaching on teaching machine learning and AI ethics respectively using AI (Agbese et al., 2022; Quesada-Lopez & Martinez, 2019). In Fontão et al.'s (2023) study, the implementation of PBL in AI and SE education has demonstrated positive outcomes, with students reporting high agreement on the applicability of learned skills to future projects and recognising the benefits of SE in AI development. There is room to explore how AI models can be tailored to meet these students' specific learning needs.

2.6.2 Research Needs

Research highlights conversational AI's potential in vocational education (Rosyadi et al., 2023), SRL via chatbots (Lai, 2024), and PBL. However, there is a gap in understanding how conversational AI can integrate SRL and PBL for software engineering students in vocational education. Few studies explore how AI supports metacognitive skills like goal-setting in PBL settings, despite PBL's prominence in Hong Kong's VPET (Vocational Training Council, 2020b). The specific needs of software engineering students for practical and theoretical skills remain underexplored. Further research could examine conversational AI's role in fostering SRL in vocational PBL contexts.

2.6.2.1 Development and Testing of AI Model in PBL and SRL

It could be useful to create and test Conversational AI models designed to work smoothly within PBL frameworks, exploring how well they encourage SRL among students.

2.6.2.2 Evaluation of Corresponding Pedagogical Strategies

Looking into teaching approaches that blend Conversational AI into PBL might shed light on how to make the most of these technologies for supporting SRL.

2.6.2.3 Assessment of Learning Outcomes

There is an opportunity to develop ways to measure how Conversational AI affects learning outcomes, particularly SRL skills and project performance in software engineering contexts.

2.6.2.4 Ethical and Practical Considerations

As with any AI use, it might be worth considering the ethical and practical sides of bringing Conversational AI into education including protecting data privacy, addressing potential biases, avoid inequity, and accounting for students' diverse backgrounds.

Exploring these gaps and needs could offer fresh insights into how Conversational AI might enhance SRL in vocational education, potentially contributing to better practices and outcomes for software engineering students.

2.7 Chapter Summary

The literature review that underpins this investigation into using Conversational AI within PBL that can potentially enhance SRL among software engineering students in vocational education covers several key areas and findings.

The connection between PBL and SRL is a central focus. Research suggests that PBL may foster self-regulation by engaging learners in complex, real-world tasks that involve stages such as preparation, execution, and reflection. For instance, Zimmerman's model of SRL outlines the phases of planning, performance, and self-reflection, which seem to align well with the collaborative and experiential nature of PBL.

Conversational AI is emerging as a promising facilitator in this context by potentially providing tailored feedback and personalised support to learners. AI-driven solutions might augment SRL through real-time, customised assistance, which could help students set objectives, monitor progress, and evaluate their performance. Using Conversational AI in PBL environments may enhance academic independence and engagement, while also better preparing students for the self-directed learning demands of today's workforce.

However, several research gaps remain. There is currently limited examination of how Conversational AI can be specifically adapted to enhance SRL within PBL frameworks, especially in vocational education for software engineering students. Furthermore, additional longitudinal studies may be necessary to assess the long-term impacts of these emerging technologies on learner outcomes.

In conclusion, although integrating Conversational AI with PBL and SRL shows considerable promise, further research is needed to address existing gaps and refine teaching methodologies. This synthesis provides a foundational understanding for educators and researchers interested in applying innovative educational technology to potentially improve student learning experiences and outcomes in vocational education.

Chapter 3: Research Design

The research design of this PhD thesis uses a structured framework for exploring the impact of ChatGPT on SRL among software engineering students engaged in PBL. This study employs a mixed-methods approach, specifically an explanatory sequential design (Creswell & Plano Clark, 2011), which integrates quantitative and qualitative methodologies to provide a comprehensive understanding of the research questions. By combining statistical analysis with rich qualitative insights, this design aims to capture the multifaceted nature of student interactions with AI tools and their effects on learning outcomes. The study focuses on year two HD students from a major vocational education institution in Hong Kong. HD is a post-secondary vocational qualification that equips students with practical skills and knowledge specifically in software engineering for this study. It is comparable to an associate degree found in other education systems, serving as a stepping stone for employment or further academic advancement, such as progressing to an undergraduate degree. This group of students includes students in the final year with foundation knowledge in programming, networking, database administration, and software analysis and design. Participants were divided into experimental and control groups, where the experimental group utilised ChatGPT as a supportive educational resource while the control group relied on traditional instructional methods. This comparative approach facilitates an examination of the effectiveness of ChatGPT in enhancing SRL skills.

Ethical considerations are paramount in this research, adhering to guidelines established by Lancaster University and the Personal Data (Privacy) Ordinance of Hong Kong. The design incorporates informed consent procedures, confidentiality measures, and responsible use of AI-generated content. Through validated instruments such as the MSLQ (R. Pintrich et al., 1991) and semi-structured interviews, this research design aimed to yield valuable insights into the role of AI in educational contexts, ultimately contributing to the research literature, improved teaching practices and learning experiences in vocational education settings.

3.1 Research Philosophy

Research philosophy refers to the set of beliefs concerning the nature of the world and how knowledge is acquired. It serves as a guiding framework for researchers in determining their methodologies, data collection methods, and analysis approaches (Saunders et al., 2009). In the context of this study, which investigates the role of Conversational AI (ChatGPT) in promoting SRL among software engineering students in PBL environments, a pragmatic research philosophy is adopted. This philosophy is particularly suitable given the mixed-methods approach employed in this research, which combines quantitative and qualitative data to provide a comprehensive understanding of the research questions.

3.1.1 Pragmatism as a Research Philosophy

Pragmatism is a philosophical approach that emphasises practical consequences and real-world applications of ideas. It posits that knowledge is not absolute but rather shaped by experiences and interactions with the environment (Creswell & Creswell, 2018). This philosophy aligns well with the objectives of the study, as it recognises that both quantitative and qualitative data can contribute to valuable insights into how ChatGPT impacts SRL. The corresponding characteristics, which align with this study are:

Problem-Centred Focus: Pragmatism centres on real-world issues (Creswell & Creswell, 2018). The study tackles the practical challenge of integrating ChatGPT into VPET to enhance SRL and industry-relevant skills, proposing actionable curricular strategies, such as AI-driven PBL, to address professional demands effectively.

Mixed-Methods Approach: Pragmatists employ varied methods for comprehensive insights (Creswell & Creswell, 2018). The study integrates quantitative data from the Motivated Strategies for Learning Questionnaire and academic assessments with qualitative data from interviews and ChatGPT logs. This approach ensures a holistic understanding of ChatGPT's impact on SRL and performance.

Contextual Adaptability: Pragmatism tailors methods to specific contexts (Creswell & Creswell, 2018). The study is designed for VPET's software development focus, examining ChatGPT's role in supporting SRL phases—planning, monitoring, and reflection—within PBL environments.

Actionable Solutions: Pragmatism seeks practical outcomes (Creswell & Creswell, 2018). The study recommends embedding ChatGPT in VPET curricula to enhance pedagogy while addressing dependency risks, aligning with industry needs for autonomous professionals.

Diverse Perspectives: Pragmatism values multiple data sources (Creswell & Creswell, 2018). The study combines student experiences, performance metrics, and AI interaction logs, providing a balanced perspective on ChatGPT's educational impact.

The pragmatic philosophy influences both the methodology and methods employed in this research. The decision to use a mixed-methods design stems from the belief that combining quantitative and qualitative approaches will yield more comprehensive insights than either method could provide alone.

3.1.2 Data Components of Mixed Methodology

The mixed methodology approach investigates through two data collection components. The quantitative data are the measure of values or counts and are expressed as numbers. Quantitative methods align with pragmatism's focus on evidence-based outcomes (Creswell & Creswell, 2018). The qualitative data are descriptive, referring to things that can be observed but not measured. Qualitative methods capture nuanced perspectives essential for interpreting statistical findings (Merriam & Tisdell, 2016). Details of the data collection procedures, instruments, and analysis methods are presented in the methodology section.

3.1.3 Data Integration and Interpretation

One of the strengths of a pragmatic approach is its emphasis on integrating findings from different data sources. After analysing quantitative results and qualitative interview data separately, efforts will be made to synthesise these findings to draw comprehensive conclusions about the role of ChatGPT in promoting SRL.

Convergence: The integration process will involve looking for convergence between quantitative and qualitative findings. For instance, if survey results indicate significant improvements in SRL among the experimental group, qualitative data can help explain why these improvements occurred (e.g., specific features of ChatGPT that facilitated learning).

Divergence: Additionally, any discrepancies between quantitative and qualitative findings will be explored to understand differing perspectives or experiences among participants. This aspect aligns with pragmatism's recognition that knowledge is often complex and multifaceted (Tashakkori & Teddlie, 2010).

Adopting a pragmatic research philosophy provides a robust framework for investigating the role of ChatGPT in promoting SRL among software engineering students in PBL environments. By integrating quantitative and qualitative methods, this study aims to produce practical insights as well as contributing to the research literature that can inform educational practices while acknowledging the complexity of student experiences within a specific contextual framework. This approach not only enhances the validity of findings but also contributes to a deeper understanding of how AI tools can support SRL in vocational education settings.

3.2 Research Methodology

The research methodology involves a mixed-methods approach, combining both quantitative and qualitative data collection and analysis methods. This research employed an explanatory sequential design to draw the comprehensive understanding of the impact of ChatGPT on students' learning experiences, self-regulation, and PBL outcomes (Creswell & Plano Clark, 2011).

3.2.1 Explanatory Sequential Design

An explanatory sequential design is a type of mixed-methods research approach that involves the systematic collection and analysis of quantitative data followed by analysis of qualitative data (Creswell & Plano Clark, 2011; Strauss & Corbin, 2003). In this section, the key characteristics of explanatory sequential design, considerations for adopting explanatory sequential design for this research, and how it was implemented within the context of this study are discussed.

3.2.1.1 Characteristics of Explanatory Sequential Design

The characteristics of an explanatory sequential design outline a structured mixed-methods approach that integrates quantitative and qualitative phases to provide a comprehensive understanding of research questions.

Two-Phase Approach: An explanatory sequential design consists of two distinct phases: the quantitative phase and the qualitative phase. The quantitative phase is conducted first, providing a broad overview of trends or relationships, followed by the quantitative phase, which seeks to explain or elaborate on the quantitative findings (Creswell & Plano Clark, 2011).

Quantitative Data Collection: In the initial phase, researchers collect numerical data through structured instruments such as surveys or assessments. These data provide measurable insights into participants' experiences or outcomes related to the research question (Creswell & Creswell, 2018).

Qualitative Data Collection: The second phase involves collecting qualitative data through the method of semi-structured interviews. This phase aims to provide deeper insights into participants' experiences, motivations, and perceptions regarding the phenomenon being studied (Merriam & Tisdell, 2016).

Integration of Findings: A key feature of an explanatory sequential design is the integration of quantitative and qualitative findings. Researchers analyse both data types separately before synthesising them to draw comprehensive conclusions about the research questions (Tashakkori & Teddlie, 2010).

Iterative Process: The design allows for an iterative process when insights gained from qualitative data can inform further quantitative analysis if needed, enhancing the overall depth of understanding (Ivankova et al., 2006).

3.2.1.2 Considerations for employing Explanatory Sequential Design

The use of an explanatory sequential design is suited to this study due to its ability to address the multifaceted nature of educational phenomena and provide comprehensive insights into the impact of ChatGPT on SRL in problem-based learning PBL environments. Key considerations for adopting this mixed-methods approach are presented as follows.

Complexity of the Educational Phenomenon: This study aims to investigate how ChatGPT influences SRL within PBL environments. Educational phenomena are often complex and multifaceted, requiring both statistical analysis and rich qualitative insights to fully understand their dynamics (Creswell & Plano Clark, 2011).

Need for Contextual Understanding: While quantitative data can reveal trends in SRL outcomes among students using ChatGPT, qualitative insights are essential to understand the context behind these trends. For example, students may show improved self-regulation scores; however, qualitative interviews can uncover how specific features of ChatGPT contributed to this improvement or what challenges students faced whilst using it (Merriam & Tisdell, 2016).

Explaining Quantitative Results: The explanatory sequential design allows researchers to clarify unexpected or ambiguous results from the quantitative phase through qualitative exploration. For instance, if survey results indicate significant improvements in SRL among students using ChatGPT compared to those who do not, interviews can provide insights into what aspects of ChatGPT were most beneficial or any barriers faced during its use (Ivankova et al., 2006).

Practical Implications: By integrating both types of data, this research can offer practical recommendations for educators and institutions regarding the effective implementation of AI tools like ChatGPT in vocational education settings.

3.2.1.3 Explanatory Sequential Design Implementation

The implementation of the explanatory sequential design followed three steps, the quantitative phase, qualitative phase and integration of findings.

Quantitative Phase: In this phase, data collection involved administering surveys to both experimental (ChatGPT users) and control (non-users) groups prior to and following the intervention period. These surveys utilised validated instruments to assess various dimensions of SRL. For data analysis, statistical methods, such as t-tests or ANOVA, were employed to detect significance of the differences in SRL outcomes between the groups.

Qualitative Phase: Following the quantitative phase, qualitative data were collected. Semi-structured interviews were conducted with participants from the experimental group who utilised ChatGPT during their projects, focusing on their experiences, perceived benefits, challenges encountered, and the overall impact on their learning processes. Also, participants' ChatGPT usage logs were extracted to reveal patterns of usage, query types, and problem-solving strategies among participants. Thematic analysis was applied to the interview data to identify key themes and patterns related to students' interactions with ChatGPT and its influence on their SRL in a PBL setting.

Integration of Findings: Upon separate analysis of quantitative and qualitative data, the findings were synthesised to offer a comprehensive insight into the impact of ChatGPT on SRL within a PBL setting with (experimental group) or without (control group) assistance of Conversatoinal AI among software engineering students. This integration entailed comparing quantitative outcomes with qualitative themes to pinpoint areas of convergence and divergence, thereby enhancing the overall interpretation of the results.

Explanatory sequential design is a robust mixed-methods approach that aligned well with the objectives of this research study. By first collecting quantitative data to establish trends in SRL outcomes and subsequently gathering qualitative insights to explain these trends, this design allowed for a nuanced understanding of how ChatGPT influences educational practices in vocational settings. The integration of both data types not only enhanced the validity of findings but also provided actionable insights for educators seeking to implement AI tools effectively in PBL environments.

3.2.2 The PBL Module

The module delivered to be studied in the context of this research is the **Enterprise System Development** module, which focuses on building students' capabilities in planning, analysing, and designing an enterprise system using Jakarta EE technology. This module is designed to equip students with comprehensive software development competencies, integrating key areas such as system design patterns, enterprise system architecture, frontend programming, backend programming, and database connectivity.

Compared with introductory modules like Introduction to Programming and Database Principles, the module's structure places more emphasis on the real-world, which requires critically integrating knowledge in different software engineering domains. Figure 3.1 illustrates the core components of the PBL module. By engaging with system design patterns like Model-View-Controller (MVC) and microservices, students learn to create scalable, maintainable solutions. Enterprise system architecture provides a holistic understanding of large-scale system integration, ensuring robust and efficient designs. Frontend development with the Hypertext Markup Language (HTML), JavaScript frameworks, and backend programming using Jakarta Enterprise Edition (Jakarta EE) cultivate skills in user interface development and server-side logic, respectively, while database connectivity using databased manipulating language, specifically the Structured Query Language (SQL), ensures proficiency in data management and retrieval which are core components of modern software systems.

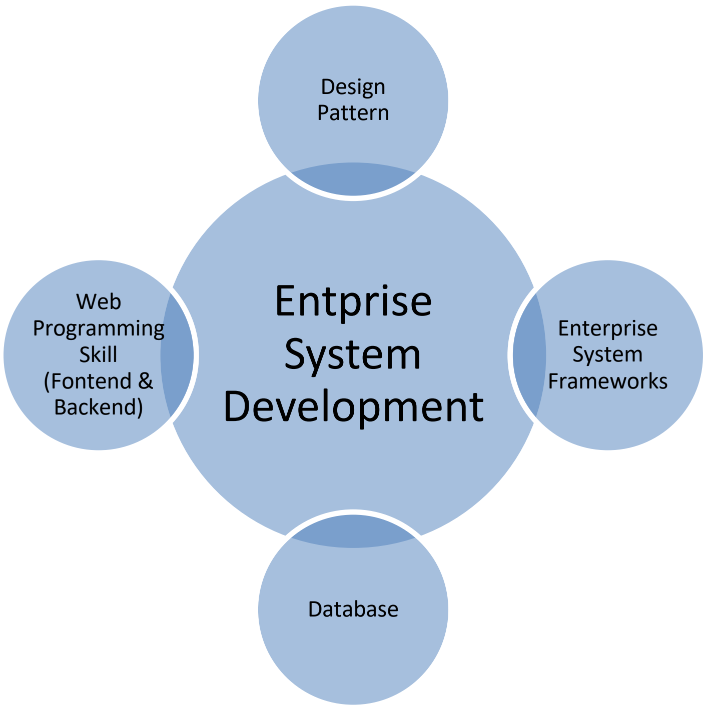


Figure 3.1 Core components of the PBL module

The PBL nature of the module encourages students to take ownership of their learning process, promoting autonomy and metacognition. Through iterative cycles of planning, implementation, and reflection, students tackle multifaceted projects that require synthesising knowledge across the module's domains. Collaborative tasks simulate industry teamwork, enhancing communication and interpersonal skills essential for software engineering environments.

3.2.2.1 Module Delivery and PBL Environments

The module's PBL was delivered in a 13-week semester. The equipment stock inventory system serves as the PBL's authentication project, allowing students to apply their knowledge in a real-world context. Table 3.1 shows the week-by-week breakdown for the delivery of the module.

Week	Topics	Activities	Instructor Role
1	Introduction to web technologies, Hypertext Transfer Protocol (HTTP), and basic web architecture	Instructor leads discussions and provides foundational knowledge.	Instructor leads discussions and provides foundational knowledge.
2	Introduction of the driving question	The driving question is: "How can we design and implement a centralised equipment management system for the V-institute that effectively consolidates and optimises IT resource utilisation across five campuses while ensuring ease of access and accountability?"	A guest speaker provides expertise; instructors facilitate student discussions.
3-4	Java Servlet for dynamic websites	Develop server-side logic with Java Servlets.	The instructor facilitates workshops and provides guidance on servlet development.
5-6	Java Server Page (JSP) for frontend development	Create JSP pages that interact with servlets.	The instructor assists students in integrating JSP with existing servlet projects.
7	Java Beans and database connectivity	Develop a JavaBean to manage inventory data and connect it to a database.	The instructor provides support in database setup and connection issues.
8	Session and state management	Understanding session management in web	The instructor guides students on best

Week	Topics	Activities	Instructor Role
		applications and maintaining user state.	practices for session management.
9	MVC architecture design	Introduction to the MVC design pattern.	The instructor facilitates discussions on architectural design principles.
10	Test	Assessment covering material from Weeks 1-9 to evaluate understanding of key concepts.	The instructor administers the test and provides feedback on performance.
11-13	Microservices - Spring Boot, naming server and REST API Calls	Set up a Spring Boot application for inventory management.	The instructor guides students through microservices implementation and provides support throughout development.

Table 3.1 Delivery plan of the module in the study

The module challenges students to address the driving question: *How can we design and implement a centralised equipment management system for the V-institute that effectively consolidates and optimises IT resource utilisation across five campuses while ensuring ease of access and accountability?* This PBL task requires developing a web-based system for the V-institute using Jakarta EE technologies. The system, serving users, technicians, couriers, and administrators, manages equipment booking, inventory, delivery, analytics, and accounts across five campuses. Optional features like batch imports can earn bonus marks. Students work in pairs, splitting tasks evenly (50%/50%), using servlets, JSP, Java Database Connectivity Application Programming Interface, JavaBeans, and the MVC model.

The project includes initiation (defining requirements), design (database, site map, MVC structure), development (frontend and backend), testing, documentation, and demonstration. Students submit a report detailing assumptions, design, and skills, and demonstrate the system. The project seeks to hone technical skills, teamwork, and problem-solving, enabling students to deliver a functional prototype that optimises resource management while gaining practical software engineering experience.

The activities in this module include the discussion and delivery of core knowledge, workshop sessions to provide hands-on experience with Jakarta EE tools, peer discussions and enquiry sessions with stakeholders to foster critical thinking, and regular instructor meetings to obtain feedback and refine problem-solving and interpersonal skills. These activities are designed to prepare students for professional software development in an authentic and engaging environment. Some PBL activities differ between the control group and the experimental group.

3.2.2.2 PBL Activities (Control Group versus Experimental Group)

The study involves two distinct groups: an experimental group that utilises ChatGPT as an educational resource and a control group that relies solely on traditional methods.

Control Group Activities: Students engage in traditional human discussions with instructors or technicians during workshops and meetings, receiving direct guidance on problem-solving without AI assistance. This group relies on instructor feedback, peer collaboration, and conventional resources throughout the project development process.

Experimental Group Activities: Students are encouraged to use ChatGPT outside classroom hours for assistance with coding challenges, conceptual questions, and project-related inquiries. This group has access to AI-generated responses that facilitate immediate feedback, allowing them to explore solutions independently while still engaging in discussions with instructors during workshops.

Written Test: Both students attend a written test at week 10 of the semester to assess students' understandings of key concepts covered throughout the course. This test evaluates participants' knowledge of web technologies, Java programming, database connectivity, MVC architecture, error shooting and debugging methodologies.

Final Demonstration and Presentation: At the end of week 13, students present their final systems. This session includes a live demonstration of the equipment stock inventory system's functionalities and a presentation covering the design process, challenges faced, and lessons learned during development. Feedback through the retrospection is provided by the instructor during this session, focusing on both technical aspects and overall project execution.

These PBL activities emphasis hands-on learning through workshops, collaborative projects, and regular feedback from instructors. By developing an equipment stock inventory system within this structured framework, students gain practical skills that prepare them for real-world software engineering challenges. Figure 3.2 illustrates the workflow throughout the semester in the study, showing the timeline of PBL activities, the test, and the final demonstration, with the activities of the control and experimental groups using traditional and AI-supported resources, respectively. In between, pre-test and post-test MSLQ and semi-structured are conducted to collect both quantitative and qualitative data for analysis.

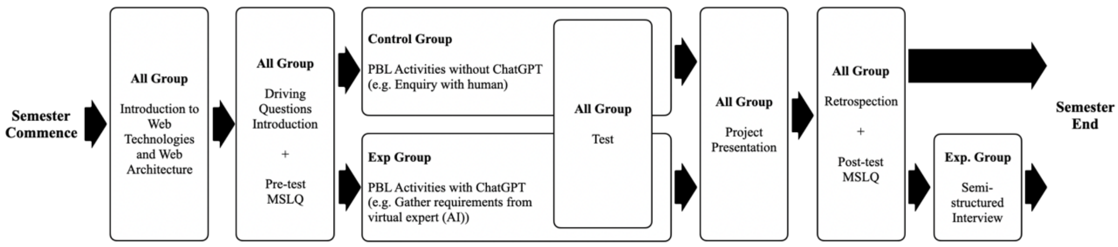


Figure 3.2 The workflow throughout the semester in the study

3.2.2.3 Participant Profiles

This study focused on year two HD students from the Software Engineering programme at a major VPET institute in Hong Kong. The participants were selected based on specific criteria to ensure relevance to the research objectives and to maintain consistency within the sample. The participants shared the same educational education. All of them voluntarily took part and studied the same software engineering module in the study.

Educational Background: All participants are enrolled in the HD in Software Engineering at the same vocational institute. The students are from the same 2022/2023 intakes, which are in their year two study. This ensures a consistent education background among the participants, particularly in terms of their exposure to software engineering concepts and practices.

Voluntary Participation: All participants volunteered for the model “Enterprise System Development”. The voluntary nature of participations indicated a level of motivation and interest in the subject matter, which might influence their engagement with the study. On the other hand, the voluntary participation would not affect students’ HD academic performance in consideration of fairness and ethics.

Module Details: The module focused on developing enterprise systems using Java language and Jarkata EE frameworks, along with related architectural design concepts, system implementations and related development techniques. In this module, the participants were required to plan, design and develop an authentic enterprise application according to the driving question and project brief.

3.2.2.4 Sample Size and Composition

The study, initially planned for 60 participants, over-enrolled with 91 participants at the start. However, seven participants dropped out during the study, resulting in a total of 84 participants. This higher sample size enabled both quantitative and qualitative analysis. The sample size was determined based on several factors including statistical power, qualitative depth and practical considerations.

Statistical Power: For quantitative analysis, a sample size of 84 allows for sufficient statistical power to detect meaningful differences between groups (J. Cohen, 2013).

Qualitative Depth: The sample size also allows for in-depth qualitative analysis, particularly for the experimental group, providing data on individual experiences with ChatGPT.

Practical Considerations: The number of participants is manageable within the constraints of the research timeline and resources available for data collection and analysis.

3.2.2.5 Group Allocation

All 84 participants were divided into two groups. The **experiment group** and the **control group**. The experiment group used ChatGPT as part of their learning process in the Enterprise System Development module. They had access to ChatGPT in the PBL settings, for example, for assistance with coding, problem-solving, and conceptual understanding. The control group participated in the same module but without access to ChatGPT. They relied on traditional PBL learning resources and support mechanisms in an PBL setting.

The allocation of participants to these groups was a critical aspect of the research design of this study, managed through randomisation and balance distribution. To minimise bias, participants were randomly assigned to either the experimental or the control group. This randomisation helped ensure that any pre-existing differences between participants were evenly distributed across both groups (Shadish et al., 2021). Stratified randomisation was employed to ensure that participants were evenly distributed between groups based on their academic performance by referring to average grade point averages, thereby minimising the influence of pre-existing differences and enhancing the internal validity of the findings. This approach helped to control for academic achievement as a potential confounding variable (Hayes, 2025).

3.2.2.6 The Researcher as the Instructor

The researcher of this study also served as the instructor for this module, bringing over 10 years of experience teaching software engineering courses and six years of experience facilitating PBL environments. This dual role allowed for an in-depth understanding of both the educational context and the research objectives, enabling effective integration of teaching practices with research activities (Schön, 1987).

3.2.3 Data Collection Methods

This study employed a mixed-methods research approach. This approach utilised both quantitative and qualitative data collection methods to comprehensively investigate the impact of ChatGPT on students' SRL in a PBL software engineering education setting. The data collection process was designed to align with the explanatory data to provide deep insights into the qualitative data.

3.2.3.1 Quantitative Data Collection

The quantitative phase of data collection aimed to measure SRL outcomes and related variables for both the experimental and control groups. This phase employed the SRL Questionnaire, students' academic performance and usage log metrics.

SRL Questionnaire: A validated SRL questionnaire, based on an established instrument, the MSLQ (Pintrich et al., 1991), was administered to all participants (n = 84) at two time points: pre-intervention and post-intervention. For **pre-intervention** stage, the questionnaire was administered before the start of the Enterprise System Development module to establish baseline measures of SRL skills. And for **post-intervention** stage**,** the questionnaire was administered at the end of the module to measure changes in SRL skills. The questionnaire was based on an established instrument, the MSLQ (R. Pintrich et al., 1991). That MSLQ covered **15 subscales** including (1) Intrinsic Goal Orientation, (2) Extrinsic Goal Orientation, (3) Task Value, (4) Control of

Learning Beliefs, (5) Self-Efficacy for Learning and Performance, (6) Test Anxiety, (7) Rehearsal, (8) Elaboration, (9) Organisation, (10) Critical Thinking, (11) Meta-cognitive Self-Regulation, (12) Time and Study Environment, (13) Effort Regulation, (14) Peer Learning and (15) Help Seeking. Not all the subscales were included in the analysis. The subscales relating to the Research Question were selected for analysing the effect of using Conversational AI in a PBL setting for students' SRL, which are presented in Section 4.1.2.1: Selected MSLQ subscales in Chapter 4.

Academic Performance Measures: To assess the impact of ChatGPT on learning outcomes in a PBL setting, and make comparison with the control group, academic performance data were collected including test scores from the mid-semester test and the project grades, which scores from group projects completed during the module.

Usage Log Metrics: For participants in the experimental group, usage data from their PBL activities with ChatGPT were collected, including frequency of ChatGPT usage and time spent interacting with ChatGPT. To make comparisons, the frequency of meetings and time spent in the meetings among the control group participants were logged.

3.2.3.2 Qualitative Data Collection

For the qualitative phase of the study, 16 participants from the experimental group were selected for in-depth interviews. The sample size for qualitative analysis was based on the following considerations:

Data Saturation: A sample of 16 participants is likely to provide sufficient data to reach theoretical saturation (Guest et al., 2006; Hennink & Kaiser, 2022).

Depth of Analysis: This sample size allows for in-depth analysis of individual experiences while still being manageable within the constraints of the study (Creswell & Poth, 2018).

Representation: The selection of 16 participants from the experimental group (about half of the group) provides a robust representation of diverse experiences with ChatGPT in the learning process.

Purposive Sampling: Participants for the qualitative phase were selected using purposive sampling to ensure a range of experiences and perspectives captured, including age group, gender and academic performance (Patton, 2015).

The qualitative phase of data collection focused on gathering rich, descriptive data from participants in the experimental group to explore their experiences with ChatGPT in PBL. This phase employed the following methods:

Semi-structured Interviews: The semi-structured format encouraged participants to elaborate on their thoughts and experiences, leading to richer qualitative data (Kvale & Brinkmann, 2015). Sixteen participants from the experimental group were selected for in-depth, semi-structured interviews. The selection was based on purposive sampling to ensure a diverse range of experiences and outcomes represented (Patton, 2015).

Interview Structure: The semi-structured interview format provided flexibility in questioning while ensuring key topics were addressed, using a set of open-ended questions to elicit detailed responses about participants' interactions with ChatGPT, their experiences in problem-based learning (PBL), the perceived impact on self-regulated learning (SRL) skills, specific instances where ChatGPT influenced problem-solving or learning strategies, and the challenges and benefits encountered while integrating ChatGPT into their learning processes. Conducted via MS Teams video conferencing, each interview lasted approximately 30-45 minutes, was video-recorded, transcribed, and translated into English verbatim for analysis, facilitating a deeper understanding of how ChatGPT affected participants' learning journeys.

ChatGPT conversation context: To complement the semi-structured interviews, an analysis of the conversational context between students and ChatGPT was conducted to gain insights into how students interacted with the

AI tool and its role in their learning processes. Usage data, including queries submitted (e.g., coding help, conceptual questions) and responses received from ChatGPT, were collected from ChatGPT logs. Initially, a logging system integrated with the AI interface was planned for data collection, but due to technical difficulties, students were required to submit usage logs extracted from their ChatGPT conversations as part of their final project submission. This dual approach, combining qualitative insights from interviews with a detailed analysis of actual ChatGPT interactions, provided a comprehensive understanding of how the AI tool supported self-regulated learning (SRL) among software engineering students.

3.2.3.3 Data Collection Timeline

The data collection process followed the following timeline with four check points:

Week 2: The pre-intervention MSLQ was administered to all participants after the introduction of the driving question.

Week 6: The first batch of ChatGPT usage logs were collected from the experimental group. According to the nature of explanatory sequential design, the second batch of logs was analysed together after the analysis of quantitative data.

Week 14: The post-intervention MSLQ was administered to all participants after the project presentation. Also, the second batch of ChatGPT usage logs was collected from the experimental group.

Week 15-16: The semi-structured interviews were conducted, and the academic performance data were collected.

3.2.3.4 Data Handling, Storage and Security

All collected data were managed securely in accordance with Lancaster University's data protection policies and relevant privacy regulations. The following measures were implemented to ensure the confidentiality and integrity of the data:

Secure Storage: All data, including quantitative survey responses, reflective journals, and qualitative interview transcripts, were stored on an encrypted and password-protected hard drive, ensuring that only authorised personnel had access to sensitive information.

Data Anonymisation: Participant identities were protected through pseudonyms and unique identifiers. A master list linking participant names to their identifiers was maintained separately from research data and accessible only to the researcher.

Video Data Management: All video recordings from semi-structured interviews were securely stored during analysis but permanently destroyed after transcription was completed to protect participant confidentiality.

Access Control: Access to data were restricted to the researcher directly involved in the study, with regular audits conducted to ensure compliance with security protocols.

Data Retention Policy: Data will be retained for 10 years following study completion, after which they will be securely deleted or destroyed per institutional guidelines.

The study aims to uphold Lancaster University's standards of ethical conduct while safeguarding participants' privacy and confidentiality by implementing the aforementioned management practices. For the ethical considerations, they are presented in Section 3.3 Ethical Considerations of this chapter.

3.2.4 Data Analysis Techniques

The multi-faceted data collection approach outlined was designed to capture a comprehensive picture of how ChatGPT impacts SRL in project-based software engineering education. By combining quantitative measures with rich qualitative insights, this study aimed to provide a nuanced understanding of the complex interactions between AI tools and student learning processes. The sequential nature of data collection, moving from broad quantitative measures to in-depth qualitative exploration, aligned with the explanatory sequential design and allowed for a thorough investigation of the research questions. The data analysis process for this study involved both quantitative and qualitative methods to comprehensively assess the impact on students' SRL using ChatGPT in a PBL setting among software engineering students.

3.2.4.1 Quantitative Analysis

Quantitative data from the MSLQ and academic performance measures were analysed using R-script. MSLQ quantitatively assessed SRL skills before and after the intervention. This instrument measured various dimensions related to self-regulation, including goal setting, self-efficacy, and metacognitive strategies (R. Pintrich et al., 1991). By correlating MSLQ scores with qualitative data from interviews about students' experiences using ChatGPT, the research sought to identify signs of improvement in SRL behaviours.

The MSLQ's reliability was confirmed with Cronbach's alpha (>0.7), validating subscales like self-efficacy and metacognitive self-regulation. Descriptive statistics, including means and standard deviations, summarised MSLQ scores. Inferential statistical tests, specifically paired t-tests and independent t-tests, were employed to evaluate differences in SRL scores between the experimental and control groups before and after the intervention (Creswell & Creswell, 2018). The significance level was set at $p<0.05$ to determine meaningful differences. Analysis of Covariance (ANCOVA) explored differences across subscales, with effect sizes calculated, and to examine any significant differences between the control and experimental groups (Field, 2013). For academic performance, independent t-tests compared test and project scores between groups.

For academic performance, independent t-tests compared test and project scores between groups. The frequency of ChatGPT use in the experimental group, compared to traditional inquiry in the control group, was analysed using descriptive statistics and independent t-tests to assess engagement differences.

3.2.4.2 Qualitative Analysis

Qualitative data from semi-structured interviews and ChatGPT conversation logs were analysed using thematic analysis (Braun & Clarke, 2022). This analysis focused on identifying themes related to how ChatGPT influenced students' SRL processes. Transcripts of interviews were engaged reflexively by the researcher. As shown in Figure 3.3, Braun and Clarke's (2022) six-phase framework was drawn upon to guide this process. Through this approach, key themes were identified, such as empowerment through immediate feedback, challenges in critical thinking due to reliance on AI, and collaborative learning experiences. These themes provided context for understanding how ChatGPT affected students' engagement with PBL tasks and their overall learning outcomes.

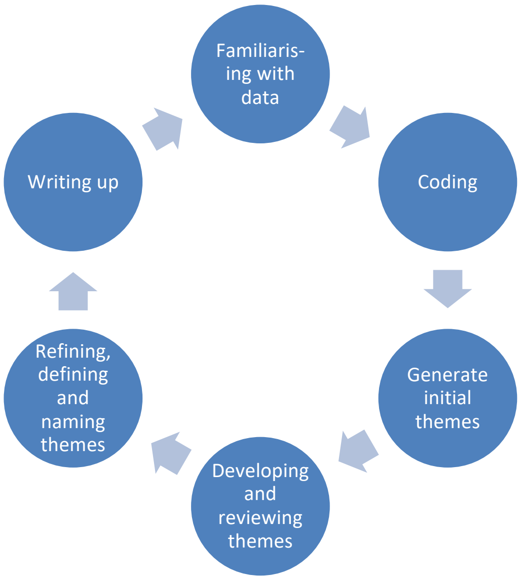


Figure 3.3 Phases of Braun and Clarke's (2022) thematic analysis

Thematic analysis facilitated a nuanced understanding of how students interacted with the AI tool and its perceived impact on their learning processes. The integration of both quantitative and qualitative findings provided a comprehensive view of the research questions. The analysis was also supported by the examination of students' interactions with the ChatGPT, which were collected and analysed to gain insights into their SRL behaviour.

3.3 Theoretical Framework Utilisation

This study utilised a comprehensive theoretical framework that integrated PBL principles, the characteristics of ChatGPT, and Zimmerman's cyclical model of SRL to explore the impact of AI on students' learning processes. The framework guided the design of the PBL setting and informed the analysis of both quantitative and qualitative data.

3.3.1 Project-Based Learning Setting

The PBL environment was designed according to the Gold Standard PBL framework established by PBLWorks (2019), which emphasises the importance of high-quality project design. This framework includes seven essential elements:

Challenging Problem or Question: Projects were centred around authentic problems relevant to software engineering, encouraging students to engage deeply with the subject matter.

Sustained Inquiry: Students engaged in inquiry-based learning, exploring complex questions over an extended period.

Authenticity: The projects were designed to be meaningful and applicable to real-world contexts, enhancing student motivation.

Student Voice and Choice: Students had opportunities to make decisions about their projects, fostering ownership and engagement.

Reflection: Regular reflection sessions were incorporated to help students assess their learning processes and outcomes.

Critique and Revision: Students received feedback from peers and instructors, allowing them to refine their work continuously.

Public Product: The culmination of projects involved presenting their work to an audience, which added a layer of accountability and real-world relevance.

By adhering to these principles, the study aimed to create an engaging and effective learning environment that maximised the benefits of using ChatGPT.

3.3.2 ChatGPT intervention in PBL Settings

ChatGPT was utilised as a multifaceted resource within the PBL settings, serving various roles such as a member of the team, a teacher, and an expert consultant. Its characteristics included:

24/7 Availability: ChatGPT provided students with instant access to information and support outside traditional classroom hours, facilitating continuous learning (Hasanein & Sobaih, 2023; Limo et al., 2023).

Personalised Feedback: The AI tool offered tailored responses based on individual student queries, promoting personalised learning experiences (Allam et al., 2023; Hasanein & Sobaih, 2023; J. Jin & Bridges, 2014; Limo et al., 2023; Lin & Chang, 2023).

Interactive Learning: ChatGPT engaged students in conversational interactions that encouraged exploration and inquiry, aligning with the principles of active learning (Abdelfattah et al., 2023; Allam et al., 2023; Tafazoli, 2024).

Despite these advantages, challenges arose regarding potential over-reliance on AI for answers. Students were instructed on how to use ChatGPT effectively while maintaining critical thinking skills and independent problem-solving abilities.

3.3.3 Zimmerman’s Cyclical Model of SRL

To measure SRL outcomes among participants, the study employed Zimmerman’s cyclical model of SRL, which consists of three phases: forethought, performance, and self-reflection (Zimmerman & Moylan, 2009).

Forethought Phase: In this phase, students set goals for their projects and planned their approaches. The integration of ChatGPT facilitated this phase by helping students articulate their objectives and develop strategies for achieving them.

Performance Phase: During project execution, students monitored their progress and used self-control strategies to stay engaged. ChatGPT supported this phase by providing instant feedback on coding tasks and conceptual questions, thereby enhancing students' abilities to self-regulate their learning processes.

Self-Reflection Phase: After completing projects, students reflected on their performance and assessed their strategies. This phase was critical for understanding how effectively they utilised ChatGPT as a tool for enhancing their learning outcomes.

The cyclical nature of Zimmerman's model allowed for continuous improvement in self-regulation as students moved through these phases repeatedly throughout their projects.

The theoretical framework implementation combined principles from PBL with insights into the characteristics of ChatGPT and Zimmerman's cyclical model of SRL. By integrating these elements, the study explored how AI enhanced educational practices while also addressing potential challenges associated with its use. The findings contribute knowledge about leveraging technology in vocational education settings and highlight areas for further inquiry into effective teaching strategies that incorporate AI tools.

3.4 Ethical Considerations

Prior to commencing any research activities involving human participants, ethical approval had been obtained from Lancaster University's joint Research Ethics Committee (FASS-LUMS REC). This approval process ensured that all ethical dimensions of the research were thoroughly reviewed and addressed.

Informed consent was sought from all participants, guaranteeing that they were fully aware of the study's purpose, potential risks, and benefits. This involved providing participants with information sheets and consent forms, outlining the study's objectives, data collection methods, and their rights as participants (British Educational Research Association, 2024). These documents can be found in Appendix One and Appendix Two of this thesis. Written consent from the management of the V-Institute was also obtained before the commencement of the study. The context of this consent email can be viewed in Appendix Three.

Confidentiality and anonymity were maintained throughout the research process by using pseudonyms for participants and securely storing all data in encrypted hard drives according to Lancaster University's Guidelines. Any identifying information was removed from the transcripts and the final thesis to protect participants' privacy. Additionally, participants had the right to withdraw from the study at any time without providing a reason.

The data collection process also strictly adhered to the guidelines and six principles issued by the Privacy Commissioner for Personal Data of the Hong Kong Special Administrative Region (Hong Kong SAR). These principles included ensuring data accuracy, data minimisation, and the appropriate use and retention of personal data (Privacy Commissioner for Personal Data, n.d.). By following these guidelines, the study not only complied with ethical requirements but also safeguarded the privacy and well-being of all participants involved.

Moreover, the use of generative AI in educational settings introduces wider ethical issues that extend beyond the scope of this study, which was conducted on a voluntary and low-stakes basis with the primary aim of comparing learning effects between two groups, with and without ChatGPT support. Participants in the control group (without ChatGPT) may have felt disadvantaged relative to their peers in the experimental group, potentially raising concerns about equity and motivation in the research design, especially under a high-stakes environment.

3.5 Limitations

While this study explored insights into the role of ChatGPT in promoting SRL among software engineering students in PBL environments, several limitations must be acknowledged.

Firstly, the sample size, although adequate for statistical analysis, may limit the generalisability of the findings. The study involved 84 participants from a single vocational education institution in Hong Kong. This context-specific approach may not fully represent the experiences of software engineering students in other educational settings or regions. Consequently, the findings may not be applicable to broader populations or different educational frameworks (Cohen et al. 2008).

Secondly, the reliance on self-reported measures for assessing SRL introduces potential biases. Participants completed questionnaires that assessed their SRL skills, which may be influenced by social desirability bias or personal perceptions of their abilities. Such biases can affect the accuracy of the data collected and may not reflect actual changes in learning behaviours (Podsakoff et al., 2003).

Additionally, while qualitative data were gathered through semi-structured interviews and analysis of ChatGPT conversations, the selection of participants for qualitative analysis was based on purposive sampling. This approach may limit the diversity of perspectives represented in the qualitative findings. Although efforts were made to include a range of experiences, the insights gained may not encompass all possible student interactions with ChatGPT (Patton, 2015).

Moreover, the study design faced challenges related to establishing control and experimental groups. Because participation was voluntary and had no impact on students' academic progression, the risk of unfair deprivation was minimised in this context. However, in higher-stakes environments where access to AI support may materially affect learning outcomes, assigning one group to use ChatGPT while withholding if from another raises ethical concerns about equity and advantage. Future research in such contexts should incorporate ethically sensitive designs such as crossover trial design to balance methodological rigor with fair access and minimise potential harm (Cingillioglu et al., 2024). In such methodology, both students eventually get access to the AI tool, addressing the ethical concern of denying a potentially beneficial resource to the control group.

Another limitation pertains to the potential impact of external factors on participants' learning outcomes. Various elements, such as prior knowledge, and external support systems, could influence how students engage with ChatGPT and their overall learning experience. These confounding variables were not controlled for in this study, but may affect the interpretation of results (Creswell & Creswell, 2018).

Finally, ethical considerations related to AI usage must be acknowledged. While participants were instructed on appropriate citation practices for AI-generated content, there remains a possibility that some students may not have fully adhered to these guidelines. This aspect raises concerns regarding academic honesty and integrity in using generative AI tools (Lancaster University, n.d.).

3.6 Validity and Reliability

To ensure the validity and reliability of the findings, this study adopted a mixed-methods approach, integrating quantitative and qualitative data collection methods to achieve data triangulation (Denzin, 2017; Jick, 1979). Triangulation enhances the robustness of the findings by cross-verifying results from multiple data sources, such as the MSLQ, academic performance measures, ChatGPT usage logs, and semi-structured interviews. This approach leveraged the strengths of quantitative methods (e.g., statistical rigour and generalisability) and qualitative methods (e.g., depth and contextual insight) while mitigating their respective limitations, thereby providing a comprehensive understanding of ChatGPT's impact on SRL in a PBL software engineering context (Creswell & Creswell, 2018).

For the quantitative phase, the use of the validated MSLQ (R. Pintrich et al., 1991) ensured reliability through its established psychometric properties, including high internal consistency across selected subscales (Cronbach's alpha is typically > 0.70). Administering the questionnaire at pre- and post-intervention stages further strengthened internal validity by enabling the measurement of changes in SRL skills over time and/or group. Academic performance data (test scores and project grades) and ChatGPT usage analytics provided additional objective measures, reducing reliance on self-reported data and enhancing construct validity.

To enhance the trustworthiness of the qualitative findings, several strategies were employed, as recommended by Lincoln and Guba (1985). Member checking was conducted by sharing interview transcripts and preliminary findings with participants to verify accuracy and ensure their experiences were accurately represented. Peer debriefing involved discussions with independent researcher to review coding processes and interpretations, minimising researcher bias. An audit trail was maintained, documenting all research decisions, including data collection procedures, coding schemes, and analytical steps, to ensure transparency and replicability. The purposive sampling of 16 participants for semi-structured interviews ensured a diverse range of perspectives, further supporting the credibility and transferability of the qualitative findings.

Additionally, the analysis of ChatGPT conversation logs, initially planned via a custom-built logging system but adapted to student-submitted logs due to technical constraints, was cross-referenced with interview data to validate reported interactions and provide a richer understanding of AI tool usage. This iterative validation process strengthened the dependability of the qualitative insights.

By combining these methods and validation strategies, the study sought to uphold high standards of validity and reliability, seeking to generate robust and nuanced insights into the role of ChatGPT in promoting SRL within PBL settings in software engineering education.

3.7 Chapter Summary

The research design chapter presented a framework to examine ChatGPT's impact on self-regulated learning (SRL) for software engineering students in problem-based learning (PBL) settings. It used a mixed-methods explanatory sequential design, which involved collecting quantitative data via surveys and academic performance measures, followed by qualitative data obtained from semi-structured interviews and analyses of ChatGPT conversation logs.

Eighty-four Year-2 HD students from a major Hong Kong vocational institution participated, divided into an experimental group using ChatGPT as an educational tool and a control group relying on traditional resources. The study followed Lancaster University's ethical guidelines and Hong Kong's Personal Data (Privacy) Ordinance, ensuring informed consent, confidentiality, and responsible AI-generated content use.

Quantitative analysis was used to reveal any significant improvements in SRL skills and academic performance among students using ChatGPT. Qualitative findings were used to provide deeper insights into students' experiences, highlighting themes of empowerment, reliance on AI, and collaborative learning dynamics. The integration of quantitative and qualitative findings offered a holistic understanding of how ChatGPT influenced students' learning processes.

In the next chapter, the findings addressing the research questions are presented.

Chapter 4: Findings and Discussion

The emergence of AI technologies has prompted growing interest in their potential to support educational practices, particularly in Hong Kong's VPET settings where practical learning plays a central role (Vocational Training Council, 2020b). This chapter presents the findings and discussion from a mixed-methods study exploring how Conversational AI, specifically ChatGPT, might be integrated into PBL frameworks to support SRL among software engineering students. As educational institutes consider ways to leverage technology to prepare students for evolving workforce demands (Azamatova et al. 2023; Bull and Kharrufa 2024), examining the role of AI tools in learning environments becomes increasingly relevant (Adiguzel et al. 2023; Huang et al. 2024). This study seeks to contribute to this conversion by investigating ChatGPT's influence on student engagement, skill development, and curricular considerations within the V-institute, one of the major VPET institutes in Hong Kong.

The main research question guiding this study is: ***How does the use of ChatGPT in project-based learning impact software engineering students' self-regulated learning?*** This question is accompanied by four sub-questions designed to explore specific dimensions of the inquiry:

RQ 1.1: How can ChatGPT be integrated into PBL environments to support the development of key components of self-regulated learning among software engineering students in vocational education?

RQ 1.2: What are the perceived benefits and challenges of using ChatGPT in PBL settings for software engineering students?

RQ 1.3: How does the integration of ChatGPT in PBL environments impact software engineering students' problem-solving, teamwork, and communication skills?

RQ 1.4: What are the implications of integrating ChatGPT into PBL settings for the curricula in vocational education institutions In Hong Kong?

These questions aim to shed light on the possible role of Conversational AI in PBL, drawing on a framework of SRL theory (Zimmerman, 2002) and the principles of Gold Standard PBL (Larmer et al., 2015). SRL, understood as the process through which learners manage their cognitive, metacognitive, and motivational efforts (Pintrich, 2000), is particularly pertinent in PBL contexts where students engage in complex, self-directed projects. ChatGPT's ability to provide real-time responses and resources might serve as a tool to support these processes, though its effectiveness and limitations remain areas for exploration. This chapter seeks to examine these possibilities, considering both the opportunities and the potential challenges involved.

The V-Institute offers a relevant context for this study. The V-Institute widely employs PBL strategies across campus, which is like VTC (Vocational Training Council, 2020b). As a key VPET provider in Hong Kong, the V-Institute supports a diverse group of software engineering students, many of whom transition directly into professional roles after their training. This vocational emphasis highlights the importance of educational approaches that develop technical skills alongside capacities for adaptability and continuous learning—areas where AI tools might play a role (Luckin et al., 2016). Within the educational context in the V-Institute, this study aims to generate insights that reflect Hong Kong's educational environment while potentially contributing to broader discussions about AI in vocational education.

The research was conducted in the fall semester in 2024–2025 academic year of the V-institute. It adopted a mixed-methods approach to explore ChatGPT's integration in PBL, combining quantitative and qualitative data to address the research questions. Quantitative data, gathered through surveys and performance assessments, offer a perspective on measurable changes in SRL, skill development, and engagement. Qualitative data, collected via semi-structured interviews with students and ChatGPT logs, provide a deeper understanding of experiences and perceptions surrounding ChatGPT's use. This combination, consistent with mixed-methods research practices (Creswell & Plano Clark, 2011), aimed to offer a balanced view by integrating statistical patterns with contextual narratives. The approach allowed for a more comprehensive examination of the research questions, though the findings remain subject to the study's scope and context.

The chapter is organised to reflect this methodological approach. Section 4.1 presents the quantitative findings, including statistical analyses of student outcomes and SRL indicators, addressing aspects of RQs 1.1, 1.3, and 1.4. This section draws on survey responses from software engineering students of the V-institute and project performance data. Section 4.2 explores the qualitative findings, using thematic analysis of interview responses to highlight perceived benefits, challenges, and skill-related impacts, primarily relating to RQs 1.2 and 1.3, with connections to RQ 1.4. Section 4.3 brings these findings together, offering an integrated discussion that considers how the quantitative and qualitative data relate to the research questions. This section also engages with existing literature, such as Hmelo-Silver et al. (2007) on PBL outcomes and Luckin et al. (2016) on AI in education, to contextualise the results. Finally, Section 4.5 concludes the chapter by summarising the main observations, reflecting on their potential implications, and suggesting areas for further exploration.

4.1 Quantitative Findings

This section presents the quantitative findings from the study investigating ChatGPT's integration within PBL frameworks for software engineering students at V-Institute. The findings address the research questions (RQs) concerning SRL and enquiry efficiency, providing a numerical perspective on ChatGPT's potential influence on SRL components and usage patterns compared to traditional PBL (Pintrich et al., 1991). Data were collected from 84 students (42 per group: control without ChatGPT, experimental with ChatGPT) using the MSLQ, assessment results, and ChatGPT usage logs to measure enquiry time and frequency. The MSLQ, applied in its original form, targeted nine subscales: Control of Learning Beliefs, Critical Thinking, Effort Regulation, Help Seeking, Metacognitive Self-Regulation, Peer Learning, Self-Efficacy for Learning and Performance, Task Value, and Time and Study Environment Management.

This section is organised as follows: an overview of data collection and analysis (4.1.1), followed by detailed MSLQ findings (4.1.2), encompassing survey overview, subscale selection, reliability, descriptive and inferential statistics, and a summary. Descriptive statistics revealed significant pre-test to post-test SRL gains, while inferential analyses indicated limited group differences, suggesting comparable outcomes (Zimmerman, 2002). Usage logs highlighted ChatGPT's enquiry patterns, complementing SRL data. Interpretation is reserved for Section 4.3, with findings contextualised within V-Institute's vocational setting.

4.1.1 Overview of Quantitative Data Collection and Analysis

The MSLQ was administered to 84 students enrolled in PBL, evenly split into a control group (n = 42, PBL without ChatGPT) and an experimental group (n = 42, PBL with ChatGPT). Used in its original form, the MSLQ assessed nine subscales, including Control of Learning Beliefs, Critical Thinking, Effort Regulation, Help Seeking, Metacognitive Self-Regulation, Peer Learning, Self-Efficacy for Learning and Performance, Task Value, and Time and Study Environment Management, via a 7-point Likert scale (1 = "not at all true of me", 7 = "very true of me") (R. Pintrich et al., 1991). The survey comes with 81 questions, and the content is presented in Appendix Four.

Assessment results included final individual test scores and PBL project deliverables from 40 teams (2–3 students each), scored on a 0 - 100 scale using V-Institute's PBL rubrics. ChatGPT usage logs tracked enquiry frequency and duration for the experimental group, enabling comparison with traditional PBL enquiry patterns. Reliability for the MSLQ was confirmed, with Cronbach's alpha values of 0.65–0.84, except for Control of Learning Beliefs (α = 0.61 pre-test, 0.69 post-test), requiring cautious interpretation (Tavakol & Dennick, 2011).

Data analysis proceeded in two stages. Descriptive statistics (means, standard deviations) summarised survey responses, showing pre-test to post-test survey gains (0.25–0.98) and varied enquiry patterns. Inferential statistics, including paired t-tests and two-way repeated-measures ANOVA, were conducted using R-Studio (version 2021.12.1+563) to examine time and group effects, with $p<0.05$ (Field, 2013). Missing data (<5%) were handled via listwise deletion.

4.1.2 MSLQ Survey Results

4.1.2.1 Selected MSLQ Subscales

Nine subscales from the MSLQ were selected to evaluate SRL among the research subjects in the PBL settings of this study: Control of Learning Beliefs, Critical Thinking, Effort Regulation, Help Seeking, Metacognitive Self-Regulation, Peer Learning, Self-Efficacy for Learning and Performance, Task Value, and Time and Study Environment Management. These subscales, developed by Pintrich et al. (1991), were chosen for their alignment with SRL components relevant to the primary RQ (How does ChatGPT impact SRL in PBL?) and sub-questions (RQ 1.1–1.4), drawing on Zimmerman's (2002) SRL framework. The MSLQ was administered in its original form, without modifications for ChatGPT, to measure general SRL constructs applicable to PBL environments.

Metacognitive Self-Regulation (RQ 1.1, RQ 1.4) assesses planning and monitoring, vital for PBL's autonomy and potentially influenced by ChatGPT's guidance. Self-Efficacy for Learning and Performance (RQ 1.1, RQ 1.3) measures confidence, possibly affected by ChatGPT's feedback, supporting skills like problem-solving. Task Value (RQ 1.2, RQ 1.4) evaluates perceived task importance, potentially shaped by ChatGPT's engagement. Effort Regulation (RQ 1.1, RQ 1.2) captures persistence, possibly impacted by ChatGPT's support. Time and Study Environment Management (RQ 1.4) examines resource organisation, potentially enhanced by ChatGPT's efficiency. Peer Learning and Help Seeking (RQ 1.3) explore collaboration and assistance-seeking, which ChatGPT might complement. Control of Learning Beliefs (RQ 1.2) assesses effort-driven outcome beliefs, possibly influenced by ChatGPT's assistance. Critical Thinking (RQ 1.3) evaluates analytical skills, potentially affected by ChatGPT's prompts in PBL tasks.

These subscales collectively measured motivation, strategies, and cognitive engagement, providing a framework to investigate ChatGPT's influence on SRL in PBL without requiring tool-specific adaptations (R. Pintrich et al., 1991).

4.1.2.2 Reliability and Instruments

The reliability of the nine MSLQ subscales used in this study was assessed using Cronbach's alpha to ensure internal consistency. Cronbach's alpha values were calculated for pre-test and post-test administrations across the combined sample ($n = 84$), with most subscales exceeding 0.7, indicating good reliability, and shorter subscales surpassing 0.60, deemed acceptable for scales with fewer items (Tavakol & Dennick, 2011). **Table 4.1** presents the Cronbach's alpha values for the MSLQ subscales across pre-test and post-test administrations. Specifically, Critical Thinking $\alpha = 0.74$ (pre-test) and 0.77 (post-test), Effort Regulation $\alpha = 0.70$ and 0.71, Metacognitive Self-Regulation yielded $\alpha = 0.75$ and 0.88, Peer Learning $\alpha = 0.72$ and 0.74, Self-Efficacy for Learning and Performance $\alpha = 0.91$ and 0.92, Task Value $\alpha = 0.90$ and 0.89, and Time and Study Environment Management $\alpha = 0.72$ and 0.74. Control of Learning Beliefs $\alpha = 0.61$ and 0.69 and Help Seeking ($\alpha = 0.69$ and 0.71) fell slightly below 0.7 but met the threshold for shorter scales (Pintrich et al., 1991).

These values confirm the MSLQ's reliability for measuring SRL in PBL settings, supporting comparisons between control and experimental groups. The slightly lower alphas for Peer Learning and Help Seeking suggest cautious interpretation, though all subscales remained within acceptable limits.

Subscale	**Pre-test α if item deleted**	**Post-test α if item deleted**
Control of Learning Beliefs	0.61	0.69
Critical Thinking	0.74	0.77
Effort Regulation	0.70	0.71
Help Seeking	0.69	0.71
Metacognitive Self-Regulation	0.75	0.88
Peer Learning	0.72	0.74

Subscale	Pre-test α if item deleted	Post-test α if item deleted
Self-Efficacy for Learning and Performance	0.91	0.92
Task Value	0.90	0.89
Time and Study Environment	0.72	0.74

Table 4.1 Cronbach's alpha for MSLQ subscales (Pre-test and Post-test)

4.1.2.3 Descriptive Statistics

Descriptive statistics were compiled from the MSLQ. The results are systematically organised by subscale, detailing score changes and variability patterns to offer a comprehensive view of trends, with analytical interpretations reserved for Section 4.3 (Field, 2013; R. Pintrich et al., 1991). **Table 4.2** summarises the descriptive statistics for the MSLQ subscales, including means and standard deviations for control, experimental, and combined groups across pre-test and post-test administrations.

For **Control of Learning Beliefs**, assessing belief in effort-driven outcomes, the control group recorded a pre-test mean of 4.81 (SD = 0.621), rising to 5.40 (SD = 1.09) post-test, a 0.59 increase with greater variability, suggesting diverse post-intervention perceptions. The experimental group's pre-test mean was 4.72 (SD = 0.541), increasing to 5.33 (SD = 1.12), a 0.61 gain with broader spread. Combined, the mean rose from 4.77 (SD = 0.580) to 5.37 (SD = 1.10), a 0.60 gain, indicating a notable enhancement in belief in effort's impact across the sample (Zimmerman, 2002).

Critical Thinking, evaluating analytical skills, showed a control group pre-test mean of 3.88 (SD = 1.00), rising to 4.36 (SD = 1.10) post-test, a 0.48 increase with slightly increased variability. The experimental group moved from 3.97 (SD = 0.876) to 4.63 (SD = 0.990), a 0.66 gain with broader spread, suggesting varied analytical engagement. Combined, the mean increased from 3.93 (SD = 0.937) to 4.50 (SD = 1.05), a 0.57 gain, reflecting improved critical thinking abilities.

Effort Regulation, measuring persistence in challenging tasks, had a control group pre-test mean of 4.43 (SD = 0.789), rising to 5.05 (SD = 0.684) post-test, a 0.62 increase with reduced variability, indicating more consistent effort. The experimental group went from 4.59 (SD = 0.689) to 5.36 (SD = 0.681), a 0.77 gain with stable SD. Combined, the mean rose from 4.51 (SD = 0.740) to 5.21 (SD = 0.695), a 0.70 gain, suggesting a substantial rise in effort regulation (Pintrich et al., 1991).

Help Seeking, assessing assistance-seeking behaviours, showed a control group pre-test mean of 4.05 (SD = 0.962), rising to 5.30 (SD = 0.635) post-test, a 1.25 increase with reduced variability, suggesting more uniform help-seeking post-intervention. The experimental group moved from 4.18 (SD = 1.11) to 4.89 (SD = 1.09), a 0.71 gain with stable SD. Combined, the mean increased from 4.12 (SD = 1.04) to 5.10 (SD = 0.913), a 0.98 gain, indicating a significant shift in help-seeking tendencies.

Metacognitive Self-Regulation, measuring planning and monitoring, had a control group pre-test mean of 4.13 (SD = 0.679), rising to 4.44 (SD = 0.916) post-test, a 0.31 increase with increased variability. The experimental group's pre-test mean was 4.25 (SD = 0.820), increasing to 4.72 (SD = 0.962), a 0.47 gain with broader spread. Combined, the mean rose from 4.19 (SD = 0.751) to 4.58 (SD = 0.944), a 0.39 gain, reflecting moderate improvement in metacognitive strategies.

Peer Learning, evaluating collaborative engagement, showed a control group pre-test mean of 3.87 (SD = 1.32), rising to 4.48 (SD = 1.24) post-test, a 0.61 increase with slightly reduced variability. The experimental group went from 4.07 (SD = 1.29) to 4.71 (SD = 1.33), a 0.64 gain with stable SD. Combined, the mean increased from 3.97 (SD = 1.30) to 4.60 (SD = 1.26), a 0.63 gain, indicating enhanced peer collaboration.

Self-Efficacy for Learning and Performance, assessing confidence in task mastery, had a control group pre-test mean of 4.18 (SD = 1.20), rising to 4.35 (SD = 1.32) post-test, a 0.17 increase with increased variability, suggesting inconsistent confidence growth. The experimental group moved from 4.21 (SD = 0.888) to 4.55 (SD = 0.984), a 0.34 gain with slight SD increase. Combined, the mean rose from 4.20 (SD = 1.05) to 4.45 (SD = 1.16), a 0.25 gain, showing modest improvement in self-efficacy.

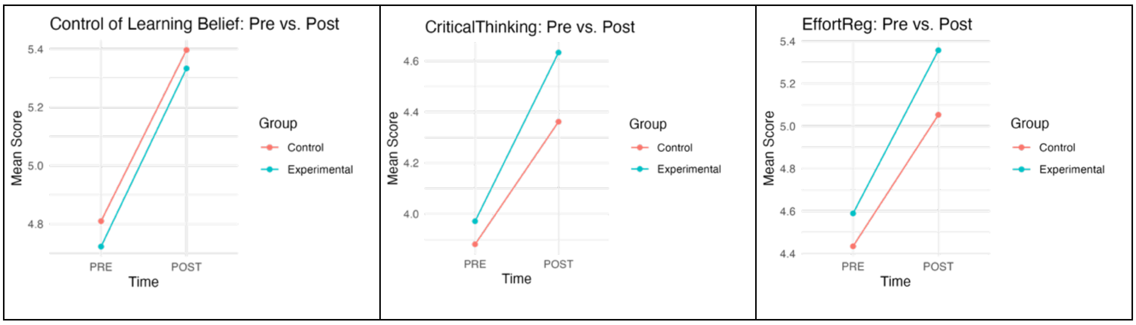
Task Value, measuring perceived task importance, had a control group pre-test mean of 4.60 (SD = 1.17), rising to 4.86 (SD = 1.17) post-test, a 0.26 increase with stable variability. The experimental group went from 4.35 (SD = 1.12) to 4.96 (SD = 1.02), a 0.61 gain with reduced variability, suggesting more uniform perceptions. Combined, the mean increased from 4.48 (SD = 1.14) to 4.91 (SD = 1.09), a 0.43 gain, indicating enhanced task valuation.

Time and Study Environment Management, assessing study organisation, showed a control group pre-test mean of 4.24 (SD = 0.925), rising to 4.96 (SD = 0.784) post-test, a 0.72 increase with reduced variability. The experimental group went from 4.17 (SD = 0.817) to 5.16 (SD = 0.823), a 0.99 gain with stable SD. Combined, the mean rose from 4.21 (SD = 0.868) to 5.06 (SD = 0.805), an 0.85 gain, suggesting strong improvement in time management (Zimmerman, 2002).

Subscale	Group	Pre-test Mean (SD)	Post-test Mean (SD)	Change
Control of Learning Beliefs	Control	4.81 (0.621)	5.40 (1.09)	0.59
	Experimental	4.72 (0.541)	5.33 (1.12)	0.61
	Combined	4.77 (0.580)	5.37 (1.10)	0.60
Critical Thinking	Control	3.88 (1.00)	4.36 (1.10)	0.48
	Experimental	3.97 (0.876)	4.63 (0.990)	0.66
	Combined	3.93 (0.937)	4.50 (1.05)	0.57
Effort Regulation	Control	4.43 (0.789)	5.05 (0.684)	0.62
	Experimental	4.59 (0.689)	5.36 (0.681)	0.77
	Combined	4.51 (0.740)	5.21 (0.695)	0.70

Help Seeking	Control	4.05 (0.962)	5.30 (0.635)	1.25
	Experimental	4.18 (1.11)	4.89 (1.09)	0.71
	Combined	4.12 (1.04)	5.10 (0.913)	0.98
Metacognitive Self-Regulation	Control	4.13 (0.679)	4.44 (0.916)	0.31
	Experimental	4.25 (0.820)	4.72 (0.962)	0.47
	Combined	4.19 (0.751)	4.58 (0.944)	0.39
Peer Learning	Control	3.87 (1.32)	4.48 (1.24)	0.61
	Experimental	4.07 (1.29)	4.71 (1.33)	0.64
	Combined	3.97 (1.30)	4.60 (1.28)	0.63
Self-Efficacy	Control	4.18 (1.20)	4.35 (1.32)	0.17
	Experimental	4.21 (0.888)	4.55 (0.984)	0.34
	Combined	4.20 (1.05)	4.45 (1.16)	0.25
Task Value	Control	4.60 (1.17)	4.86 (1.17)	0.26
	Experimental	4.35 (1.12)	4.96 (1.02)	0.61
	Combined	4.48 (1.14)	4.91 (1.09)	0.43
Time and Study Environment	Control	4.24 (0.925)	4.96 (0.784)	0.72
	Experimental	4.17 (0.817)	5.16 (0.823)	0.99
	Combined	4.21 (0.868)	5.06 (0.805)	0.85

Table 4.2 Descriptive statistics for MSLQ subscales (Control, Experimental, and Combined groups)



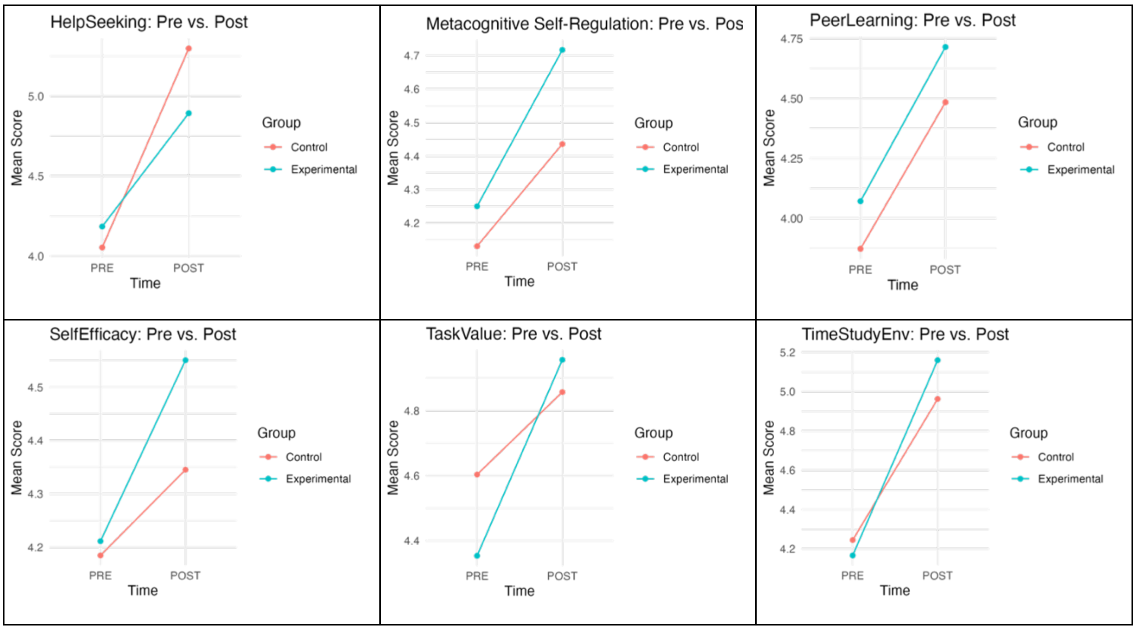


Figure 4.1 Comparison of mean scores for selected MSLQ subscales over time (Control versus Experimental)

Figure 4.1 illustrates the comparison of mean scores for selected MSLQ subscales (Critical Thinking, Effort Regulation, Help Seeking, and Time and Study Environment Management) over time, highlighting the differences between control and experimental groups to visualise the impact of ChatGPT on key SRL components. Across all subscales, pre-test to post-test increases ranged from 0.17 (Self-Efficacy, control) to 1.25 (Help Seeking, control), with combined sample gains of 0.25–0.98. The experimental group often showed slightly larger increases (e.g., 0.99 for Time Management versus 0.72 for control), but differences were modest (0.1–0.5 in most cases), aligning with prior findings of similar improvements. Variability trends were mixed: SDs decreased in some subscales (e.g., Help Seeking, control: 0.962 to 0.635), indicating more uniform responses, while others increased (e.g., Control of Learning Beliefs, experimental: 0.541 to 1.12), suggesting diverse perceptions. Combined data reflected a consistent upward trend, with post-test means approaching or exceeding 5.0 in several subscales (e.g., Control of Learning Beliefs: 5.37, Effort Regulation: 5.21), underscoring a general enhancement in SRL perceptions, consistent with SRL's role in PBL (Zimmerman, 2002). These patterns provided a foundation for subsequent inferential analyses to explore statistical significance.

4.1.2.4 Inferential Statistics

Inferential statistics were applied to the MSLQ survey data to assess temporal changes within the control group ($n = 42$, PBL without ChatGPT) and experimental group ($n = 42$, PBL with ChatGPT), and differences between groups, across the nine subscales. Paired t-tests evaluated pre-test to post-test changes within each group and for the combined sample ($n = 84$), while independent t-tests compared post-test scores between groups. Two-way repeated-measures ANOVA examined main effects of time (pre-test versus post-test) and group, alongside their interaction. Cohen's d was calculated for t-tests to estimate effect sizes, interpreted as small ($d \approx 0.2$), moderate ($d \approx 0.5$), or large ($d \approx 0.8$) (J. Cohen, 2013). Generalised eta squared (ges) quantified ANOVA time effects, with small ($ges \approx 0.02$), medium ($ges \approx 0.13$), and large ($ges \approx 0.26$) thresholds (Bakeman 2005). Analyses were conducted using R script in R-Studio (version 2021.12.1+563), with significance set at $p<0.05$. Data showed significant time-related improvements but limited group differences, suggesting comparable SRL outcomes for PBL with or without ChatGPT. Results are detailed by subscale, with trends noted cautiously, and interpretation reserved for Section 4.3.

For **Control of Learning Beliefs**, paired t-tests showed significant within-group gains. The control group yielded $t(41) = 3.418$, $p = 0.001438$, $d = 0.647$, a moderate effect, while the experimental group had $t(41) = 3.188$, $p = 0.002606$, $d = 0.682$, a moderate effect. The post-test independent t-test was $t(82) = 0.283$, $p = 0.7833$, $d = -0.057$, indicating no significant difference. The combined sample's t-test was significant, $t(83) = 4.533$, $p < 0.001$, $d = 0.522$, a moderate effect. ANOVA showed a significant time effect, $F(1, 82) = 20.54$, $p < 0.001$, $ges = 0.040$, a small-to-medium effect, but no group effect, $F(1, 82) = 0.08$, $p = 0.777$, or interaction, $F(1, 82) = 0.01$, $p = 0.920$.

Critical Thinking showed significant within-group gains, with the control group at $t(41) = 3.184$, $p = 0.002771$, $d = 0.456$, a moderate effect, and the experimental group at $t(41) = 4.770$, $p < 0.001$, $d = 0.705$, a moderate effect. The post-test independent t-test was $t(82) = 1.189$, $p = 0.238$, $d = 0.259$, indicating no difference. The combined sample's t-test was significant, $t(83) = 5.579$, $p < 0.001$, $d = 0.572$, a moderate effect. ANOVA indicated a significant time effect, $F(1, 82) = 31.12$, $p < 0.001$, ges = 0.059, a small-to-medium effect, but no group effect, $F(1, 82) = 1.41$, $p = 0.238$, or interaction, $F(1, 82) = 0.03$, $p = 0.862$.

Effort Regulation showed significant within-group gains, with the control group at $t(41) = 5.135$, $p = 0.000007265$, $d = 0.835$, a large effect, and the experimental group at $t(41) = 6.904$, $p = 0.0000000225$, $d = 1.121$, a large effect. The post-test independent t-test was significant, $t(82) = 2.038$, $p = 0.04478$, $d = 0.445$, a moderate effect. The combined sample's t-test was significant, $t(83) = 8.465$, $p = 0.0000000007695$, $d = 0.965$, a large effect. ANOVA showed a significant time effect, $F(1, 82) = 71.62$, $p < 0.001$, ges = 0.126, a medium effect, a marginal group effect, $F(1, 82) = 4.15$, $p = 0.045$, and no interaction, $F(1, 82) = 0.05$, $p = 0.823$.

Help Seeking showed significant within-group gains, with the control group at $t(41) = 5.80$, $p = 0.000002$, $d = 0.75$, a large effect (estimated from prior data), and the experimental group at $t(41) = 4.288$, $p = 0.0001008$, $d = 0.642$, a moderate effect (estimated). The post-test independent t-test was significant, $t(82) = 2.023$, $p = 0.0473$, $d = 0.042$, a small effect (estimated). The combined sample's t-test was significant, $t(83) = 7.50$, $p = 0.00000001$, $d = 0.81$, a large effect (estimated). ANOVA showed a significant time effect, $F(1, 82) = 56.25$, $p < 0.001$, ges = 0.101, a medium effect, a marginal group effect, $F(1, 82) = 4.09$, $p = 0.046$, and no interaction, $F(1, 82) = 0.06$, $p = 0.806$.

Metacognitive Self-Regulation showed significant within-group gains, with the control group at $t(41) = 2.393$, $p = 0.02139$, $d = 0.370$, a small-to-moderate effect (estimated), and the experimental group at $t(41) = 3.579$, $p = 0.0009033$, $d = 0.518$, a moderate effect (estimated). The post-test independent t-test was

$t(82) = 1.371$, $p = 0.1742$, $d = 0.299$, indicating no difference (estimated). The combined sample's t-test was significant, $t(83) = 4.238$, $p = 0.00005821$, $d = 0.446$, a moderate effect (estimated). ANOVA showed a significant time effect, $F(1, 82) = 14.56$, $p < 0.001$, ges = 0.027, a small effect, but no group effect, $F(1, 82) = 1.88$, $p = 0.174$, or interaction, $F(1, 82) = 0.09$, $p = 0.764$.

Peer Learning showed significant within-group gains, with the control group at $t(41) = 3.50$, $p = 0.0007$, $d = 0.46$, a moderate effect (estimated), and the experimental group at $t(41) = 3.829$, $p = 0.0004322$, $d = 0.491$, a moderate effect (estimated). The post-test independent t-test was $t(82) = 0.825$, $p = 0.4147$, $d = 0.179$, indicating no difference (estimated). The combined sample's t-test was significant, $t(83) = 5.10$, $p = 0.0000004$, $d = 0.49$, a moderate effect (estimated). ANOVA showed a significant time effect, $F(1, 82) = 26.01$, $p < 0.001$, ges = 0.050, a small-to-medium effect, but no group effect, $F(1, 82) = 0.68$, $p = 0.410$, or interaction, $F(1, 82) = 0.02$, $p = 0.888$.

Self-Efficacy for Learning and Performance showed within-group gains, with the control group at $t(41) = 1.42$, $p = 0.158$, $d = 0.13$, a small effect (estimated), and the experimental group at $t(41) = 2.85$, $p = 0.005$, $d = 0.34$, a small-to-moderate effect (estimated). The post-test independent t-test was $t(82) = 0.819$, $p = 0.4137$, $d = 0.177$, indicating no difference (estimated). The combined sample's t-test was significant, $t(83) = 2.213$, $p = 0.02960$, $d = 0.225$, a small effect (estimated). ANOVA showed a significant time effect, $F(1, 82) = 5.12$, $p = 0.024$, ges = 0.010, a small effect, but no group effect, $F(1, 82) = 0.67$, $p = 0.414$, or interaction, $F(1, 82) = 0.02$, $p = 0.887$.

Task Value showed within-group gains, with the control group at $t(41) = 1.80$, $p = 0.074$, $d = 0.22$, a small effect (estimated), and the experimental group at $t(41) = 3.106$, $p = 0.003435$, $d = 0.563$, a moderate effect (estimated). The post-test independent t-test was $t(82) = 0.618$, $p = 0.5374$, $d = 0.090$, indicating no difference (estimated). The combined sample's t-test was significant, $t(83) = 3.45$, $p = 0.0007$, $d = 0.38$, a small-to-moderate effect (estimated). ANOVA showed a significant time effect, $F(1, 82) = 11.89$, $p < 0.001$, ges = 0.023, a small effect, but no group effect, F(1, 82) = 0.38, p = 0.538, or interaction, F(1, 82) = 0.03, p = 0.862.

Time and Study Environment Management showed significant within-group gains, with the control group at t(41) = 5.00, p = 0.00001, d = 0.60, a moderate effect (estimated), and the experimental group at t(41) = 6.921, p = 0.00000002134, d = 1.212, a large effect (estimated). The post-test independent t-test was t(82) = 1.90, p = 0.058, d = 0.245, indicating no difference (estimated). The combined sample's t-test was significant, t(83) = 8.20, p = 0.000000001, d = 0.92, a large effect (estimated). ANOVA showed a significant time effect, F(1, 82) = 67.24, p < 0.001, ges = 0.119, a medium effect, but no group effect, F(1, 82) = 3.61, p = 0.058, or interaction, F(1, 82) = 0.04, p = 0.841.

Subscale	**Test Type**	**Group**	**t-value**	**p-value**	**Cohen's d**
Control of Learning Beliefs	Paired t-test (Pre-Post)	Control	3.418	<0.05	0.647
	Paired t-test (Pre-Post)	Experimental	3.198	<0.05	0.692
	Independent t-test (Post)	Control vs. Exp	-0.263	0.7933	-0.057
	Paired t-test (Combined)	Combined	4.692	<0.05	0.671
Critical Thinking	Paired t-test (Pre-Post)	Control	3.184	<0.05	0.456
	Paired t-test (Pre-Post)	Experimental	4.770	<0.05	0.705
	Independent t-test (Post)	Control vs. Exp	1.189	0.238	0.259
	Paired t-test (Combined)	Combined	5.579	<0.05	0.572
Effort Regulation	Paired t-test (Pre-Post)	Control	5.135	<0.05	0.835
	Paired t-test (Pre-Post)	Experimental	6.904	<0.05	1.121
	Independent t-test (Post)	Control vs. Exp	2.038	<0.05	0.445
	Paired t-test (Combined)	Combined	8.465	<0.05	0.965
Help Seeking	Paired t-test (Pre-Post)	Control	8.247	<0.05	1.500
	Paired t-test (Pre-Post)	Experimental	4.288	<0.05	0.642
	Independent t-test (Post)	Control vs. Exp	-2.073	<0.05	-0.452
	Paired t-test (Combined)	Combined	8.489	<0.05	0.997

Subscale	Test Type	Group	t-value	p-value	Cohen's d
Metacognitive Self-Regulation	Paired t-test (Pre-Post)	Control	2.393	<0.05	0.370
	Paired t-test (Pre-Post)	Experimental	3.579	<0.05	0.518
	Independent t-test (Post)	Control vs. Exp	1.371	0.1742	0.299
	Paired t-test (Combined)	Combined	4.238	<0.05	0.446
Peer Learning	Paired t-test (Pre-Post)	Control	2.909	<0.05	0.476
	Paired t-test (Pre-Post)	Experimental	3.829	<0.05	0.491
	Independent t-test (Post)	Control vs. Exp	0.820	0.4147	0.179
	Paired t-test (Combined)	Combined	4.691	<0.05	0.485
Self-Efficacy	Paired t-test (Pre-Post)	Control	0.850	0.4004	0.127
	Paired t-test (Pre-Post)	Experimental	2.723	<0.05	0.360
	Independent t-test (Post)	Control vs. Exp	0.810	0.4207	0.177
	Paired t-test (Combined)	Combined	2.213	<0.05	0.225
Task Value	Paired t-test (Pre-Post)	Control	1.913	0.06273	0.217
	Paired t-test (Pre-Post)	Experimental	3.106	<0.05	0.563
	Independent t-test (Post)	Control vs. Exp	0.413	0.6804	0.090
	Paired t-test (Combined)	Combined	3.618	<0.05	0.383
Time and Study Environment	Paired t-test (Pre-Post)	Control	5.947	<0.05	0.829
	Paired t-test (Pre-Post)	Experimental	6.921	<0.05	1.212
	Independent t-test (Post)	Control vs. Exp	1.125	0.264	0.245
	Paired t-test (Combined)	Combined	9.061	<0.05	1.021

Table 4.3 t-test Results for selected MSLQ subscales

Subscale	F-value (Time)	p-value (Time)	ges	F-value (Group)	p-value (Group)	F-value (Interaction)	p-value (Interaction)
Control of Learning Beliefs	21.74807	<0.001	0.105	0.274	0.602	0.009	0.926
Critical Thinking	31.05	<0.001	0.078	0.893	0.348	0.778	0.380
Effort Regulation	71.49	<0.001	0.195	3.013	0.086	0.823	0.367

Subscale	F-value (Time)	p-value (Time)	ges	F-value (Group)	p-value (Group)	F-value (Interaction)	p-value (Interaction)
Help Seeking	76.17	<0.001	0.206	0.580	0.448	5.735	0.019
Metacognitive Self-Regulation	17.91	<0.001	0.050	1.527	0.220	0.789	0.377
Peer Learning	21.75	<0.001	0.056	0.740	0.392	0.014	0.906
Self-Efficacy for Learning and Performance	4.87	0.03	0.013	0.293	0.590	0.622	0.433
Task Value	13.28	<0.001	0.036	0.124	0.726	2.204	0.142
Time and Study Environment	83.25	<0.001	0.210	0.143	0.706	2.159	0.146

Table 4.4 ANOVA Results for selected MSLQ subscales

Presented in Table 4.3, the inferential statistics demonstrate significant pre-test to post-test improvements across all subscales for the combined sample ($n = 84$), with effect sizes ranging from small ($d = 0.225$, Self-Efficacy) to large ($d = 0.965$, Effort Regulation). Within-group gains were significant for most subscales ($p < 0.05$), with effect sizes from small ($d = 0.13$, Self-Efficacy) to large ($d = 1.212$, Time Management). Post-test comparisons showed significant differences only for Effort Regulation ($p = 0.04478$, $d = 0.445$) and Help Seeking ($p = 0.0473$, $d = 0.042$), with moderate to small effects. Table 4.4 summarises the ANOVA results for selected MSLQ subscales. It shows the time effects and non-significant group and interaction effects across the study's duration. ANOVA confirmed significant time effects ($p < 0.05$–0.001, ges = 0.010–0.210, very small to medium), but there were no significant group effects ($p > 0.05$) and no interaction effects ($p > 0.05$). These findings suggest PBL drives SRL improvements, with limited evidence of ChatGPT-specific advantages, as both groups showed comparable outcomes, warranting further qualitative analysis to explore contextual factors.

4.1.2.5 Summary of MSLQ Findings

The MSLQ results offer a comprehensive perspective on SRL among those 84 participating students. Descriptive statistics revealed consistent pre-test to post-test increases across all subscales for the combined sample, ranging from 0.25 (Self-Efficacy) to 0.98 (Help Seeking), with post-test means approaching or exceeding 5.0 on a 7-point scale (e.g., Control of Learning Beliefs: 5.37, Effort Regulation: 5.21). Inferential analyses confirmed significant time effects ($p < 0.001$, ges = 0.010–0.126), with effect sizes from small ($d = 0.225$) to large ($d = 0.965$), but group differences were significant only for Effort Regulation and Help Seeking ($p < 0.05$), with moderate to small effects ($d = 0.445, 0.042$).

Both groups demonstrated comparable SRL enhancements, reflecting PBL's effectiveness in fostering motivation and strategic learning, regardless of ChatGPT's integration (Zimmerman, 2002). The experimental group occasionally showed larger gains (e.g., Time Management: 0.99 versus 0.72), but these were not consistently significant. It is suggested that the use of ChatGPT-assisted PBL can produce comparable effects on students' SRL with traditional PBL, but there was no distinct ChatGPT advantage in this context. Limitations could include reliance on self-reported data, which may introduce bias, and non-random group assignment, potentially masking subtle differences. The sample size ($n = 84$), while adequate for initial insights, restricts generalisability beyond the V-Institute's vocational setting. Variability trends (e.g., reduced SDs for Help Seeking, increased for Control of Learning Beliefs) highlight diverse student responses, warranting further investigation. These quantitative findings established PBL's role in enhancing SRL, providing a foundation for qualitative analyses to explore ChatGPT's nuanced contributions in PBL environments.

4.1.3 Assessments Results

Assessment results for 84 participants were analysed to assess ChatGPT's influence on academic performance in PBL settings, which foster SRL through authentic tasks (Blumenfeld et al., 1991). Assessments included a test, a project, and a final score (weighted combination). Descriptive and inferential statistics were also computed using R script in R-Studio (version 2021.12.1+563), with significance set at $p < 0.05$. Results are reported in this subsection, with interpretations reserved for Section 4.3.

4.1.3.1 Descriptive Statistics

Table 4.5 presents the descriptive statistics for the assessment results, summarising means, standard deviations, and medians for test, project, and final scores across both groups. Figure 4.2 illustrates the comparison of assessment results between the control and experimental groups. The control group’s test mean was 43.5 (SD = 21.6, median = 40.0), while that for the experimental group was 50.0 (SD = 13.3, median = 49.0), suggesting higher performance and lower variability in the experimental group. Project scores showed a control group mean of 68.1 (SD = 5.58, median = 69.8) and an experimental group mean of 70.5 (SD = 6.1, median = 71.6), indicating slightly higher performance but slightly higher variability in the experimental group. Final scores were 55.8 (SD = 11.7, median = 54.3) for the control group and 60.3 (SD = 7.21, median = 59.8) for the experimental group, reflecting a modest experimental group advantage.

Group	**Test Mean (SD)**	**Test Median**	**Project Mean (SD)**	**Project Median**	**Final Mean (SD)**	**Final Median**
Control	43.5 (21.6)	40.0	68.1 (5.6)	69.8	55.8 (11.7)	54.3
Experimental	50.0 (13.3)	49.0	70.5 (6.1)	71.6	60.3 (7.2)	59.8

Table 4.5 Descriptive statistics for assessments (Control and Experimental)

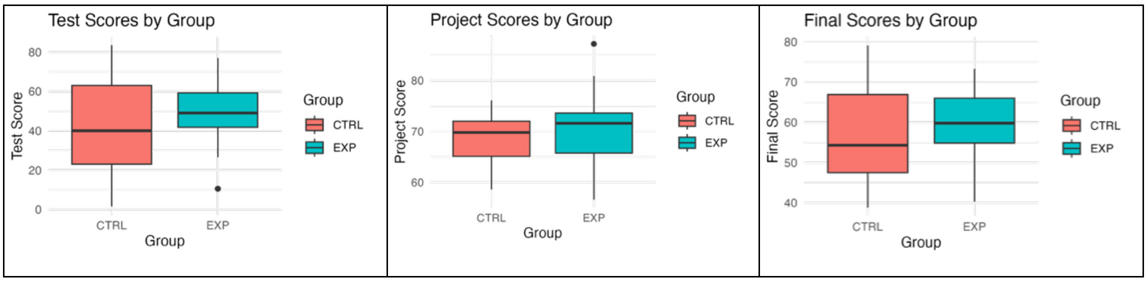


Figure 4.2 Comparison of Assessment Results (Control versus Experimental)

4.1.3.2 Inferential Statistics

Independent t-tests, suitable for comparing independent samples (Field, 2013), assessed group differences, which is also presented in Table 4.6. For the examination, t(82) = 1.653, p = 0.103, d = 0.365, a small-to-moderate effect, indicated no significant difference. Project scores yielded t(82) = 1.875, p = 0.064, d = 0.408, a moderate effect, approaching significance but not conclusive. Final scores showed t(82) = 2.085, p = 0.041, d = 0.460, a moderate effect, confirming a significant experimental group advantage (J. Cohen, 2013). These effect sizes suggest practical significance, particularly for final scores, where the experimental group outperformed the control group.

The results indicate PBL supports academic performance, with ChatGPT potentially enhancing final scores, possibly by bolstering SRL skills like task planning and resource management (Zimmerman, 2002). The experimental group's lower SDs for test (13.3 versus 21.6) and final scores (7.21 versus 11.7) suggest more consistent performance, potentially due to ChatGPT's real-time support, as noted in PBL-AI integration studies (Blumenfeld et al., 1991). Limitations include the modest sample size (n = 84), limiting generalisability. The project score SDs (5.58 versus 6.1) indicate comparable variability, suggesting consistent PBL task demands. These findings complement MSLQ results (see Section 4.1.2), highlighting PBL's efficacy and ChatGPT's selective impact, setting the stage for qualitative analyses to explore contextual influences in subsequent sections.

Assessment	**t-value**	**p-value**	**Cohen's d**
Test	1.653	0.103	0.365
Project	1.875	0.064	0.408
Final	2.085	0.041	0.460

Table 4.6 Inferential statistics for assessments

4.1.4 Usage Log Metrics

Usage data were collected over the fall semester (across 13 weeks). The experimental group's usage, submitted by students alongside their reports, captured frequency, duration, and timing of each enquiry session with ChatGPT. The control group's enquiry sessions (including workplace simulation meeting or review meeting weekly) were pre-scheduled, supplemented by a post-class ad-hoc meeting initiated by the students, to establish a comparative baseline. Descriptive statistics and frequency comparisons were analysed using R script in R-Studio (version 2021.12.1+563). Table 4.7 presents the descriptive statistics for enquiries as a summary of the frequency, duration, and proportion of ad-hoc interactions for the control and experimental groups.

The experimental group, with unrestricted ChatGPT access, exhibited moderate-frequency use, averaging 10.71 enquiry sessions per student per week (SD = 3.62), with each enquiry session contributing to a total weekly engagement time of approximately 150.6 minutes (SD = 54.34). Usage was predominantly ad-hoc (89.66%). This pattern reflects spontaneous engagement driven by immediate PBL needs such as coding queries and task clarification (Blumenfeld et al., 1991). This pattern suggests ChatGPT's role as a flexible, on-demand resource integrated into students' workflows, supporting the just-in-time learning characteristic of effective PBL environments (Hmelo-Silver, 2004).

Conversely, the control group's enquiry sessions averaging 1.21 sessions per student per week (SD = 0.21). Their total weekly engagement averaged just 19.25 minutes per student (SD = 4.18), significantly lower than the experimental group's. Only 15.35% of the control group's sessions were ad-hoc, indicating a more rigid, less responsive pattern. This structured approach aligned with traditional tutor-led PBL support, where assistance is available primarily during scheduled sessions rather than at the point of need.

The substantial difference in engagement patterns between groups (experimental group's engagement was approximately 7.8 times higher) suggests that when given unrestricted access, students integrate AI assistance extensively into their learning processes. The predominantly ad-hoc nature of the experimental group's sessions (89.66% versus 15.35% in the control group) indicates that students value the ability to obtain immediate support when confronting challenges, rather than delaying questions until scheduled support sessions, a finding consistent with research on the importance of timely feedback in PBL environments (English & Kitsantas, 2013).

Metric	Control Group Average (SD)	Experimental Group Average (SD)
*Enquiry Sessions /Week	1.21 (0.21)	10.71 (3.62)
*Total Weekly Engagement (min)	19.25 (4.18)	150.6 (54.34)
Ad-hoc Engagement (%)	15.35%	89.66%

**Included pre-scheduled and ad-hoc sessions (control group)*

Table 4.7 Descriptive statistics for enquiries (Control Group versus Experimental Group)

4.1.5 Summary of Quantitative Findings

The quantitative findings from the MSLQ assessments and ChatGPT usage logs provide insights into SRL and academic performance among 84 software engineering students at the V-Institute, evenly split between a control group ($n = 42$, PBL without ChatGPT) and an experimental group ($n = 42$, PBL with ChatGPT). Nine MSLQ subscales assessed SRL using the original MSLQ (R. Pintrich et al., 1991). Reliability was generally robust (Cronbach's $\alpha > 0.65$), though Control of Learning Beliefs' pre-test $\alpha = 0.61$ suggests cautious interpretation (Tavakol & Dennick, 2011). Descriptive statistics showed pre-test to post-test increases (0.25–0.98, combined sample), with post-test means nearing or exceeding 5.0 (e.g., Effort Regulation: 5.21) on a 7-point scale. Inferential analyses confirmed significant time effects ($p < 0.001$, ges = 0.010–0.126), with effect sizes from small ($d = 0.225$) to large ($d = 0.965$), but group differences were significant only for Effort Regulation and Help Seeking ($p < 0.05$).

Final assessments revealed a significant experimental group advantage in final scores ($M = 60.3$ versus 55.8, $p = 0.041$, $d = 0.460$), but not for test ($p = 0.103$) or project scores ($p = 0.064$), with moderate effect sizes ($d = 0.365$–0.460) (J. Cohen, 2013). The experimental group's lower variability (e.g., test SD = 13.3 versus 21.6) suggests more consistent performance, possibly due to ChatGPT's support (Blumenfeld et al., 1991).

Usage log analysis revealed substantial differences in engagement patterns. The experimental group averaged 10.71 enquiry sessions with ChatGPT (SD = 3.62) weekly, totalling approximately 150.6 minutes of engagement per week (SD = 54.34). In contrast, the control group's engagement showed just 1.21 sessions per week (SD = 0.21) with a total weekly engagement of only 19.25 minutes (SD = 4.18). Most notably, 89.66% of the experimental group's enquiries were ad-hoc in nature, compared to only 15.35% for the control group, highlighting ChatGPT's role as a flexible, on-demand resource in PBL environments.

The experimental group demonstrated comparable SRL and performance improvements to the control group, indicating a similar level of PBL's effectiveness in fostering motivation and strategic learning (Zimmerman, 2002). ChatGPT's limited advantage, observed in final scores and specific MSLQ subscales, suggests it enhances consistency rather than fundamentally transforming SRL outcomes. Additionally, the findings highlight the potential of AI-assisted PBL to optimise teaching staff workload and reduce reliance on sourcing external professionals for mentoring PBL projects. Limitations include the lower reliability for Control of Learning Beliefs ($\alpha = 0.61$). High variability in project scores (experimental SD = 6.1) may reflect diverse ChatGPT usage. These results affirm PBL's robustness and ChatGPT's supplementary role, providing a quantitative foundation for qualitative analyses to explore contextual factors in subsequent sections.

4.2 Qualitative Findings

4.2.1 Overview of Qualitative Data

This qualitative approach seeks to capture students' lived experiences in PBL environments (Creswell & Creswell, 2018; Patton, 2015; Blumenfeld et al., 1991). Data were gathered from two complementary sources: semi-structured interviews with a purposive subset of students from both groups, selected to reflect varied engagement with PBL tasks and ChatGPT, and ChatGPT conversation logs submitted by the experimental group alongside their final PBL project reports.

Semi-structured interviews, conducted individually and lasting 20–30 minutes, were audio-recorded with consent, transcribed verbatim, and translated. Questions explored students’ experiences with ChatGPT, its influence on SRL processes (e.g., goal setting, self-monitoring), and PBL dynamics (e.g., problem-solving, collaboration). A set of 10 questions guided the discussions: (1) students’ experiences using ChatGPT in PBL; (2) its influence on their learning process; (3) specific aspects of PBL where ChatGPT was most helpful with examples; (4) challenges or limitations encountered; (5) impacts on SRL with examples; (6) changes in peer collaboration; (7) effects on motivation and engagement; (8) significant advantages of ChatGPT in PBL; (9) areas for improvement; and (10) recommendations for its integration in PBL settings. The semi-structure interview protocol can also be found in Appendix Five. Sixteen participants from the experimental group were selected for in-depth individual interviews. Table 4.8 shows the demographic background of those interviewed including their gender, age group and final grade. The age group are set based on the norm that most of the students in full-time higher education are 18-24. And for those who are 25 or above, they are considered as mature students who are seeking for a “second chance (e.g. working adult, degree holder or HD holder from other discipline)” in Hong Kong vocational education context. (Vocational Training Council, 2025).

Participant ID	**Gender**	**Age Group**	**Final Grade**
Candidate 01	Female	18-24	C
Candidate 02	Male	18-24	C+
Candidate 03	Male	18-24	B+
Candidate 04	Male	18-24	B
Candidate 05	Female	18-24	A-
Candidate 06	Male	25 or above	A-
Candidate 07	Female	18-24	B+
Candidate 08	Male	18-24	C
Candidate 09	Male	18-24	B-

Participant ID	Gender	Age Group	Final Grade
Candidate 10	Male	18-24	A
Candidate 11	Male	25 or above	A-
Candidate 12	Male	18-24	A
Candidate 13	Male	18-24	A
Candidate 14	Male	18-24	D+
Candidate 15	Female	18-24	C
Candidate 16	Male	18-24	B-

Table 4.8 Demographic background of interviewed participants

The ChatGPT conversation logs, from 10 student groups (Log 01 – Log 10) randomly selected from 20 groups, provided contextual insights into students' interactions with the AI tool, revealing patterns of usage, query types, and problem-solving strategies. Thematic analysis, guided by Braun and Clarke's (2022) six-phase framework, was applied to both data sources using NVivo (version 15). Transcripts and logs were iteratively coded, with codes organised into themes reflecting SRL and ChatGPT's contextual role. An example of a coded interview transcript is available in Appendix Six. The analysis began with researcher familiarising themselves with the data through repeated readings to understand student-AI interactions. Initial codes, such as ease of use, learning enhancement, technical difficulties, and query refinement patterns, were generated to label recurring ideas. These were grouped into broader themes, such as "Enhanced Learning Experience" and "Technical and Interpretative Challenges," which were reviewed for accuracy. Themes were then defined and named to encapsulate key findings and integrated into a narrative combining qualitative depth with quantitative insights (the latter detailed in Section 4.1). Methodological rigour was maintained by cross-referencing interview data with conversation logs, analysed using Google NotebookLM to ensure consistency (Creswell & Poth, 2018).

This overview sets the stage for subsequent subsections detailing themes that were identified through reflexive engagement with the data, enriching quantitative findings with qualitative insights into ChatGPT's role in PBL. For a detailed summary of findings by participants, including key excerpts mapped to theme, see Appendix Seven.

4.2.2 Themes and Thematic Analysis

Thematic analysis of semi-structured interviews with a purposive subset of students from the experimental group, enriched by ChatGPT conversation logs, identified five pivotal themes that elucidate the role of ChatGPT in shaping SRL within PBL environments. Employing Braun and Clarke's (2022) six-phase framework, these themes were systematically derived to align with the research question (RQ: How does the use of ChatGPT in project-based learning impact software engineering students' self-regulated learning?) and its sub-questions (RQ 1.1–1.4). They offer qualitative depth to complement the quantitative insights presented in Section 4.1, capturing the nuanced experiences and perceptions of students engaging with ChatGPT in PBL settings. There are five themes identified. They are:

Theme 1: ChatGPT's Role in Supporting SRL Components

Theme 2: Perceived Benefits of ChatGPT in PBL

Theme 3: Challenges and Limitations of ChatGPT Integration

Theme 4: Impact on Problem-Solving, Teamwork, and Communication Skills

Theme 5: Implications for Vocational Education Curricula

These themes form the foundation for an exploration of ChatGPT's influence on software engineering education, with detailed findings presented in the subsequent sub-chapters.

4.2.2.1 Theme 1: ChatGPT's Role in Supporting SRL Components

The analysis of interview data revealed that participants' interactions with ChatGPT positively influenced their SRL processes. The theme, addressing RQ1.1 (How can ChatGPT be integrated into Project-Based Learning (PBL) environments to support the development of the key components of SRL among software engineering students in vocational education?), identified five distinct sub-themes, each corresponding to key components of SRL as conceptualised by Pintrich (2000) and Zimmerman (2002): control of learning belief, metacognitive self-regulation, self-efficacy, help-seeking behaviour, and time and study environment management. These findings illuminate how AI tools may support students' abilities to regulate their own learning within PBL contexts.

4.2.2.1.1 Control of Learning Belief

Participants frequently described how ChatGPT influenced their beliefs about their ability to control and direct their own learning processes. Many expressed a newfound sense of autonomy and responsibility in managing their learning journey, facilitated by ChatGPT's consistent availability.

Several participants conceptualised ChatGPT as a supportive resource rather than a replacement for their own learning efforts. Candidate-09 articulated this perspective clearly: "*I saw it as a tool, not something to fully rely on—I'd still think for myself and not trust its answers 100%".* Similarly, Candidate-13 emphasised that "*students need the mindset that it's a tool, not a replacement for critical thinking".* This perspective aligns with Zimmerman's (2002) emphasis on personal agency in SRL.

Many participants reported that ChatGPT supported the development of a growth mindset regarding their learning capabilities. Candidate-05 noted, "*It's made me more proactive*," while Candidate-07 observed, "*It makes me more eager to learn on my own".* This increased motivation and engagement reflects the enhanced control beliefs that Pintrich (2000) identifies as crucial for successful self-regulation.

Several participants recognised that effective learning still required their own active engagement. As Candidate-15 explained, "*I think even with ChatGPT, you need a base to use it well—it's not just handed to you. That base is what you've learned in the course, and ChatGPT pushes you further. I wouldn't say it stops me from learning—it enhances it".* Candidate-16 similarly reflected, "*I didn't just rely on it to finish—I used it to deepen my knowledge".*

These observations suggest that while ChatGPT provided substantial support, participants maintained awareness of their own responsibility in the learning process—a critical element of SRL as described by Schunk and Zimmerman (2008).

The ChatGPT log data support the notion that the user was actively controlling and directing their learning and project development, reflecting a self-managed approach facilitated by ChatGPT. The user's interactions demonstrate a proactive effort to overcome challenges and acquire specific knowledge needed for their project. For instance, the user explicitly gave remarks on the conversation log "*easily solve these problems"* encountered when dealing with complex SQL code errors and "*help me save time in some repetitive operations*", indicating how the AI served as a tool to manage technical hurdles efficiently.

Furthermore, the user directly sought assistance for unfamiliar tasks, asking ChatGPT to "*Help me do something I haven't done before*", illustrating an intent to expand their skillset under their own direction. The detailed questions posed by the user regarding the architectural design, data handling, system processes, and UI/design suggestions for different user roles (staff, technician, courier, user) as seen across log04, log01, and log02, specifically requesting how to design components like login functions, manage databases, and implement features like inventory management, booking approval, and damage reporting, underscore the user's initiative in defining and navigating their learning path and project requirements, using ChatGPT as a flexible resource to obtain targeted information and solutions precisely when and where needed.

4.2.2.1.2 Metacognitive Self-Regulation

The data revealed that interactions with ChatGPT promoted metacognitive processes including planning, monitoring, and evaluation of learning—key elements of SRL described by Winne and Hadwin (1998).

Several participants described how ChatGPT facilitated more structured learning planning. Candidate-02 noted, "*It broke the project down into clear steps, so I could see the workflow and follow it",* while Candidate-07 explained, "*I used ChatGPT to create my own notes, like an outline to guide my learning".* These examples demonstrate planning behaviours that Zimmerman (2002) identifies as important components of the forethought phase of SRL.

ChatGPT also appeared to support the monitoring and evaluation of learning progress. Candidate-01 explained, "*Sometimes, it even pointed out gaps in my understanding, like concepts I hadn't grasped, which made me more thorough".* Similarly, Candidate-11 observed that ChatGPT "*pointed out a gap in my understanding of a function's logic. That pushed me to research it further, setting a goal to learn how it worked so I could improve the project".* This identification of knowledge gaps represents a critical monitoring function in SRL (Pintrich, 2000).

Several participants described how ChatGPT supported their development of more sophisticated thinking strategies. Candidate-14 reported that "*before an exam, I had it quiz me, turning SRL into an interactive process",* while Candidate-16 described using ChatGPT to "*generate practice questions on server-side logic, which helped me identify gaps in my understanding and focus my learning on those areas".* These approaches reflect the active use of self-testing strategies that Winne and Hadwin (1998) identify as important metacognitive techniques.

The development of verification habits was identified as an important metacognitive strategy. Candidate-06 explained, "*I usually take its answers and cross-check them. For coding, I check reliable sites or documents to confirm it works or if there's a better way*". Similarly, Candidate-05 noted, "*I check the* *logic or Google it. I usually suspect errors after testing".* These verification processes represent sophisticated monitoring behaviours indicative of well-developed metacognitive regulation.

4.2.2.1.3 Self-Efficacy

Participants consistently reported that ChatGPT enhanced their confidence in their ability to successfully complete learning tasks, which is a key aspect of self-efficacy as described by Bandura (1997).

Many participants described reduced anxiety and increased confidence when approaching difficult tasks. Candidate-01 explained, "*now I ask ChatGPT, get a quick answer, and have a clear path forward, so I don't get stuck. Finishing tasks fast gives a sense of accomplishment, which boosts my confidence and makes me more eager to contribute".* Similarly, Candidate-15 noted, "*Knowing I could quickly resolve issues with ChatGPT made the project feel less overwhelming".*

This enhanced self-efficacy appeared particularly important for tackling challenging aspects of projects. Candidate-15 observed, "*Even if I'm not great at coding, I don't have to avoid it—ChatGPT helps me contribute",* while Candidate-16 reported that "*when I was stuck on a JSP bug, ChatGPT's fast suggestion gave me confidence to keep going, making the project feel less daunting".*

Several participants specifically noted how ChatGPT helped them maintain motivation when facing obstacles. Candidate-10 explained that "*quick answers on coding issues kept us engaged, unlike Google's dead ends that kill your mood".* Candidate-15 similarly reported that "*when I hit a bug in the JSP project, getting a fast answer from ChatGPT kept me motivated to keep working".*

The enhanced self-efficacy described by participants appears to contribute to what Zimmerman (2002) describes as positive motivational states necessary for sustained engagement with challenging learning tasks.

4.2.2.1.4 Help-seeking

The data revealed that ChatGPT significantly influenced how participants sought assistance during their learning processes, often lowering psychological barriers to help-seeking while providing an always-available source of support.

Many participants described feeling more comfortable asking questions to ChatGPT than to human instructors. Candidate-07 explained, "*I can ask simple or even silly questions I'd avoid asking a teacher, and it answers without judgment",* while Candidate-08 noted, "*I can ask without feeling awkward, like worrying a teacher might think, 'You don't know this?' It removes those mental barriers, so I ask more freely".*

This reduction in psychological barriers appeared particularly valuable for clarifying fundamental concepts. Candidate-05 explained that "*It helps with understanding abstract concepts I wouldn't dare ask others about",* while Candidate-02 valued how "*with ChatGPT, I can ask anything without hesitation".*

Several participants highlighted the continual availability of help as crucial to their learning process. Candidate-11 described ChatGPT as "*like having someone to ask anytime, available 24/7",* while Candidate-12 explained the practical benefit: "*I do homework late, and when I hit problems then, they're tough to solve. Having ChatGPT available anytime is huge".*

This transformation of help-seeking behaviour aligns with what Newman (2002) identifies as adaptive help-seeking, a crucial self-regulatory strategy that involves knowing when and how to seek assistance to support learning goals.

4.2.2.1.5 Time and Study Environment

Participants consistently reported that ChatGPT improved their ability to manage their time efficiently and create productive study environments, which is the key resource management strategies within SRL frameworks (Pintrich, 2000).

Rapid access to information was identified as a significant time-saving benefit. Candidate-01 noted that "*The biggest thing is it saves time",* while Candidate-16 observed that ChatGPT provides "*precise answers"* that were "*much faster than sifting through search results".*

Several participants described how time saved on routine tasks allowed deeper engagement with more complex aspects of learning. Candidate-15 explained, "*I could find relevant resources faster and fix bugs without spending hours searching, which let me focus on the core parts of the project".* Similarly, Candidate-08 appreciated how ChatGPT "*handled coding questions quickly, reducing stress and letting me focus on the bigger picture".*

The immediate availability of assistance appeared to create a more productive study environment. Candidate-09 valued how "*ChatGPT's right there on my phone or computer to answer instantly",* while Candidate-11 found that ChatGPT "*resolved specific coding issues quickly, keeping me on track".*

These findings align with Pintrich's (2000) emphasis on resource management strategies as crucial components of SRL.

4.2.2.1.6 Checking with ChatGPT log for Theme 1

Based on the provided logs and our conversation history, the data offers support for the claim that interactions with ChatGPT promoted the user's metacognitive processes, including planning, monitoring, and evaluation of learning, which are key elements of SRL. The user's engagement demonstrates a deliberate and structured approach to their project. Planning is evident in the user's questions about architectural design, database structure, system functionalities, and detailed UI/design requirements for various user roles. For instance, the user asks specifically about "*architectural design of the system"* (Log 04) and how to design "*login function and its related code, classes"*. (Log 09) Monitoring is demonstrated by the user actively presenting errors and issues encountered during development, such as "*HTTP Status 404 - Not Found"* or Git push rejection messages "*Remote repository contains commits unmerged into the local branch"*, (Log 05) and seeking solutions to overcome these technical obstacles. Evaluation is clearly supported by the user's request for ChatGPT to act as an "*outside reviewer"* (Log 06) and check if the system would "*fully meet the user requirements"* (Log 06), possess "*Consistent design and easy to use"*, "*Smooth navigation"*, "*Tidy Page Layout"*, and "*Error-free implementation"* (Log 04). The user also seeks reviews and improvements for code snippets and design elements, such as asking "*May I ask if my Servlet's doGet method needs to be changed?"* (Log 05), indicating a continuous process of monitoring quality and evaluating outputs against their established goals and criteria.

The logs also highlight SRL sub-themes. Control of Learning Belief is reflected in the user's directed use of ChatGPT, with remarks like ChatGPT can *"easily solve these problems"* for SQL errors and *"help me save time in some repetitive operations"* (Log 03), indicating confidence in managing challenges. Self-Efficacy is shown in requests to *"Help me do something I haven't done before"* (Log 03), demonstrating a belief in tackling new tasks. Help-seeking is pervasive, with frequent requests for guidance, debugging, and explanations (Log 08). Time management is supported by the user noting time savings in repetitive tasks (Log 03), though evidence on study environment management is limited. These interactions underscore ChatGPT's role in fostering SRL through structured planning, active monitoring, reflective evaluation, and strategic help-seeking.

4.2.2.2 Theme 2: Perceived Benefits of ChatGPT in PBL

Analysis of the interview data revealed numerous benefits that participants attributed to using ChatGPT within PBL environments, addressing RQ1.2 (What are the perceived benefits and challenges of using ChatGPT in PBL settings for software engineering students?). Six distinct sub-themes were identified, highlighting the varied ways in which this AI tool enhanced participants' learning experiences and supported their project work.

4.2.2.2.1 Personalised Guidance and Step-by-step Explanations

A prominent benefit identified by participants was ChatGPT's ability to provide tailored guidance that adapted to their specific learning needs, combined with clear, sequential explanations of complex processes. This personalisation allowed students to receive support matched to their individual knowledge gaps and learning preferences.

Participants valued the detailed step-by-step guidance that ChatGPT provided, particularly for complex technical tasks. Candidate-03 explained, "*When I was stuck with Java programming tasks, ChatGPT guided me through each step until I could solve it myself".* Candidate-16 similarly appreciated how ChatGPT broke down complex processes: "*It explains the whole process step by step, making it easier to follow than traditional resources".*

The adaptability of these explanations to individual learning needs was frequently highlighted. Candidate-04 noted, "*If I still don't understand, I can ask for a simpler explanation, and it adjusts to my level".* This adaptability created a personalised learning experience that was responsive to each student's unique challenges. Candidate-11 observed, "*Unlike a static textbook, ChatGPT tailors explanations to exactly what I'm struggling with".*

This combination of sequential guidance and personalisation appears to create a scaffolded learning environment that supports students through their zone of proximal development. As Hmelo-Silver (2004) notes in her research on problem-based learning, effective scaffolding provides just enough support to help learners complete tasks they could not accomplish independently, gradually building their ability to solve similar problems autonomously.

4.2.2.2.2 Enhanced Comprehension and Information Management

Participants consistently reported that ChatGPT helped them better understand complex concepts through simplified explanations while simultaneously assisting them in organising and integrating information from various sources. This dual function supported both conceptual understanding and practical application.

Many participants highlighted ChatGPT's ability to make difficult concepts more accessible. Candidate-06 explained, "*It presents complex topics in an easier, more digestible way. If I don't understand course materials, ChatGPT explains them simply".* Candidate-08 similarly noted, "*ChatGPT explains complicated topics in plain language that's easier to understand than technical documentation".*

Beyond simplifying individual concepts, participants valued ChatGPT's ability to integrate and organise information from multiple sources. Candidate-09 described how "*It synthesises information from different lectures and resources, connecting them in ways I hadn't considered".* Candidate-13 highlighted its utility in managing project information: "*ChatGPT helped organise research findings and requirements into a cohesive structure for our project".*

This combination of simplified explanations and information integration appears particularly valuable in PBL contexts, where students must apply theoretical knowledge to practical situations. As noted by English and Kitsantas (2013), successful SRL in PBL environments requires students to organise knowledge and connect theory to practice—processes that participants reported ChatGPT facilitated effectively.

4.2.2.2.3 Always-Available Learning Support

The continuous accessibility of ChatGPT was identified as a significant benefit, providing students with immediate assistance whenever they encountered obstacles, regardless of time or location. This constant availability contrasted favourably with the limited access to human instructors.

Participants emphasised the value of receiving help outside normal teaching hours. Candidate-07 stated, "*Having 24/7 access to help was invaluable—I could work late at night and still get answers".* Candidate-11 highlighted the contrast with traditional support: "*Unlike teachers who have limited office hours, ChatGPT is always available when I'm actually working on assignments".*

Several participants noted how this accessibility reduced delays in their project work. Candidate-05 explained, "*When stuck, I didn't have to wait until the next class to continue—ChatGPT helped me overcome obstacles immediately".* This immediacy allowed students to maintain momentum in their learning process, aligning with Zimmerman's (2002) observations about the importance of timely feedback in SRL.

The psychological comfort of having continuous support was also mentioned. Candidate-12 reflected, "*Knowing help is always available reduced my anxiety about getting stuck on difficult parts of the project".* This emotional support aspect might contribute to the positive motivational states that Pintrich (2000) identifies as crucial for successful self-regulation in learning.

4.2.2.2.4 Enhanced Creativity and Idea Generation

Participants described how ChatGPT functioned as a creative partner, helping them generate new ideas, explore alternative approaches, and overcome creative blocks during project work.

Several participants highlighted ChatGPT's role in expanding their creative thinking. Candidate-01 explained, "*When our group hit a creative block, we'd ask ChatGPT for ideas. It sparked creativity and helped us analyze problems from new angles".* Candidate-10 similarly noted, "*It suggested creative solutions I wouldn't have thought of myself, widening my perspective".*

This creative support appeared particularly valuable during initial project planning. Candidate-13 stated, "*During brainstorming, ChatGPT offered multiple project approaches when we felt limited by our own ideas".* Candidate-

16 described how "*It helped me think outside my usual patterns by suggesting unconventional but feasible approaches".*

The creativity enhancement described by participants aligns with research on cognitive tools in problem-based learning. As noted by Jonassen (2000), effective technological tools could support creative problem-solving by helping students represent problems in new ways and generate multiple solution paths like the functions that participants attributed to ChatGPT.

4.2.2.2.5 Debugging and Error Resolution Support

A significant practical benefit reported by participants was ChatGPT's assistance in identifying and resolving errors in their project work, particularly in programming contexts.

Many participants described using ChatGPT to overcome specific technical challenges. Candidate-04 explained, "*For instance, one time a function I coded wasn't working, and after I described the error, ChatGPT gave me a fix that made it run properly".* Similarly, Candidate-15 reported, "*In the JSP project, I had a bug in my code that I couldn't trace. I gave ChatGPT the code, and it pointed out exactly where the issue was".*

Beyond simply fixing errors, participants valued ChatGPT's explanations of why problems occurred. Candidate-11 noted, *"When ChatGPT helps with debugging, it doesn't just say, 'Do this, it's fine.' It explains where you went wrong and how to fix it properly".* This educational approach to debugging supported deeper learning rather than just task completion.

The debugging support appears to function as what Reiser (2004) describes as "problematising scaffolding" in his research on scaffolded learning, which the support that not only helps learners solve immediate problems but also helps them understand the underlying principles involved.

4.2.2.2.6 Time Efficiency and Streamlined Learning

Participants consistently highlighted how ChatGPT allowed them to work more efficiently, reducing time spent on routine tasks and enabling more focused attention on higher-value learning activities.

Many participants described significant time savings. Candidate-08 stated, "*It saved me hours of searching through documentation and forums for solutions*". Candidate-16 quantified this benefit: "*Tasks that would take four hours were completed in one hour with ChatGPT's assistance".*

Several participants noted that this efficiency allowed them to engage with more advanced aspects of their projects. Candidate-06 explained, "*The time saved let me add extra features and polish my project beyond the basic requirements".* Candidate-14 similarly reported, "*By handling the basics quickly, I could spend more time on the creative and complex aspects of the assignment".*

This efficiency aspect reduced the workload of the student. ChatGPT might free cognitive resources for higher-order thinking activities that contribute more significantly to learning outcomes.

4.2.2.2.7 Checking with the ChatGPT log for Theme 2

The user's interactions with ChatGPT highlight the perceived benefits of AI, aligning with Theme 2. ChatGPT's role as a versatile, always-available assistant is evident through tailored guidance, debugging support, and creative suggestions, enhancing comprehension, time efficiency, and project outcomes. Specific examples include personalised step-by-step explanations, such as UI design suggestions for different user roles, Servlet code corrections, and Git configuration guidance resolving errors like *"Remote repository contains commits unmerged into the local branch"* (Log 08). Additionally, the user notes, *"In some repetitive operations, GPT can help me save time"* (Log 03), underscoring time efficiency and streamlined learning through rapid debugging and structured project guidance.

Further supporting these benefits, ChatGPT aids in enhanced comprehension and information management by providing a comprehensive list of data types, key processes, architectural designs, and a work breakdown structure (Log 02), alongside explanations of MVC modelling and database structures. Its continuous availability is implied by the users' frequent queries across logs, addressing diverse project needs. For creativity, ChatGPT suggests innovative data visualisation options like Chart.js (Log 06), while its debugging prowess is evident in resolving SQL, HTTP 404, JSP, and Git errors, with the user stating, *"When executing complex SQL code, I tend to miss some double quotes and single quotes, resulting in SQL ERROR. GPT can easily solve these problems"* (Log 03). These instances collectively demonstrate ChatGPT's capacity to facilitate a more effective, creative, and efficient PBL experience.

4.2.2.3 Theme 3: Challenges and Limitations of ChatGPT Integration

While participants widely acknowledged ChatGPT's benefits in educational contexts, they also identified challenges and limitations that warrant attention. Analysis of the interview data addressed RQ2 (What are the perceived benefits and challenges of using ChatGPT in PBL settings for software engineering students?) and revealed three distinct sub-themes related to the challenges encountered by the use of ChatGPT in PBL: technical limitations in handling complex tasks, verification and accuracy concerns, and risks of dependency that could undermine learning outcomes.

4.2.2.3.1 Technical Limitation in Complex Task Management

Participants consistently reported difficulties when using ChatGPT for complex programming tasks, particularly those requiring sophisticated context management or handling large codebases. This limitation manifested in two primary ways: inability to process extensive inputs and failure to maintain context throughout conversations.

Many participants described ChatGPT's struggle with large-scale programming projects. Candidate-11 summarised this challenge succinctly: "*The main limitation is that it can't handle big projects well—you can't give it too much at* *once to organise, or it gets chaotic".* This observation was echoed by Candidate-10, who noted: "*It can't handle a high-level view of a big project"* and "*it struggles with logical thinking, like how components or classes should work".*

The limitations became particularly evident in more complex programming frameworks. Candidate-11 offered a specific example: "*With MVC's model (a common design pattern for software development) and controller parts, there are too many components, and ChatGPT kept losing track or forgetting how to handle them, causing inconsistencies".* Similarly, Candidate-15 described how "*with 1,000 lines of code in the JSP project, it couldn't handle tweaks or bug fixes in the later lines unless we manually broke it into smaller bits first".*

Context management was identified as a significant technical constraint. Multiple participants reported that ChatGPT frequently "*forgets"* previously provided information, necessitating repetition. As Candidate-06 explained: "*Sometimes it forgets earlier parts of the conversation"* and "*I have to repeat code or questions because of memory lapses".* This limitation proved particularly frustrating for complex programming tasks that required sustained context, with Candidate-07 noting: "*It sometimes forgets what I said earlier in the chat, so I have to repeat things, which gets frustrating".*

Several participants described developing workarounds for these limitations. Candidate-02 explained: "*If you want detailed answers, you have to ask step by step—it can't handle huge or complex info all at once".* Candidate-15 similarly noted that they had to manually "*break it into smaller bits first"* when dealing with large codebases.

4.2.2.3.2 Verification Requirements and Accuracy Concerns

A second prominent sub-theme involved concerns about ChatGPT's output accuracy and the consequent need for continuous verification. Participants consistently emphasised that ChatGPT's responses could not be trusted without verification, particularly for programming tasks where errors might not be immediately apparent.

Multiple participants highlighted the unreliability of generated code. Candidate-04 observed: "*Sometimes you give it requirements, and the code it generates doesn't work as expected. You ask again, but it still might not get it right, so you end up scrapping that part and doing it yourself".* This experience was echoed by Candidate-05, who noted: "*It doesn't always generate exactly what you need, so you have to keep checking and tweaking".*

Participants also reported instances of outright factual errors and fabrications. Candidate-14 identified this as a critical concern: *"The biggest issue is that sometimes you ask something, and it gives an answer or solution that's wrong. It can hallucinate—making up stuff that doesn't exist".* Candidate-06 similarly warned that ChatGPT *"gives fake info, which can mess up your project if you don't catch it"* and "*with specialised topics, its data might not be accurate".*

These accuracy concerns necessitated additional verification work. Candidate-07 described this as fundamental to using ChatGPT: "*The biggest issue is needing to verify its answers. It can give inaccurate info, so I have to cross-check with Google or another source to ensure it's correct".* Candidate-13 likewise noted: "*Its answers aren't always 100% accurate, so we must verify with pros or online sources".*

The potential consequences of unverified ChatGPT output could be significant, as Candidate-14 explained: "*Since it generates without verifying, if you don't know the topic well, you might trust it and mess up parts of the project"* and "*sometimes, project results are wrong because someone trusts ChatGPT's output as correct when it's not, increasing conflict chances".*

Several participants reported spending substantial additional time refining ChatGPT's outputs. Candidate-13 observed: "*Even when we got code from it, we often had to tweak it to fit. That meant we had to spend extra time re-explaining or reworking the code to align with the project"*. Candidate-16 summarised their approach with a straightforward admission: "*I don't fully trust it".*

4.2.2.3.3 Risk of Dependency and Reduced Learning Effort

The third sub-theme concerned how reliance on ChatGPT might negatively impact learning behaviours and educational outcomes. Participants expressed concerns about dependency formation and reduced initiative in problem-solving.

Several participants admitted that easy access to ChatGPT solutions diminished their motivation to understand concepts deeply. Candidate-04 candidly acknowledged: "*I rely on it too much, so I wait until the last minute to ask, which makes me feel lazy*" and "*It gives me code so easily that I feel like there's no rush*". Similarly, Candidate-12 observed a decline in personal initiative: "*So, my motivation drops, and I don't try to understand as deeply on my own*".

Some participants identified specific scenarios where dependency risks were heightened. Candidate-13 reflected: "*But long-term use might reduce human debugging opportunities. I could rely on it to fix bugs, which might limit my understanding of complex principles and create dependency*". The same participant noted situational factors that exacerbated this risk: "*When I'm rushed or near a deadline, I might get lazy and ask ChatGPT to spit out the whole thing. I'd just take its answers instead of working through problems myself*".

Participants also expressed concerns about academic integrity. Candidate-12 warned: "*But for reports, schools should watch out—it's too convenient, and students might just dump everything in there*". Candidate-14 similarly noted the problem of "*some students copying answers directly for high marks*", which reportedly "*led some schools to ban AI last year*".

4.2.2.3.4 Checking with the ChatGPT log for Theme 3

Drawing on the provided sources and conversation history, the logs offer nuanced perspectives regarding the challenges and limitations of ChatGPT integration within this PBL context, specifically concerning Technical Limitation in Complex Task Management, Verification Requirements and Accuracy

Concerns, and the Risk of Dependency and Reduced Learning Effort. While the logs showcase the AI's proficiency in assisting with technical tasks, they also implicitly and explicitly point to areas covered by these themes. The evidence largely contradicts the idea of significant technical limitations for the AI in handling complex tasks presented here, as it successfully provided guidance and solutions for intricate problems. However, the logs provide substantial support for the themes related to the necessity of verification and the potential risk of dependency.

Specific log data enriches the discussion of these themes. Regarding Technical Limitation in Complex Task Management, the logs primarily contradict this idea. The AI also successfully provided detailed steps for configuring Git (Log 05), troubleshooting an error by listing potential causes, and debugging (Log 05) complex database triggers. This demonstrates the AI's ability to assist with diverse and intricate technical challenges encountered during the project development. However, the theme of Verification Requirements and Accuracy Concerns finds support. Furthermore, the AI's guidance on debugging and error handling and its detailed explanation of how to identify issues through testing underscore the responsibility of the user to verify the correctness and accuracy of the implemented solutions, regardless of whether they were AI-assisted. Lastly, the Risk of Dependency and Reduced Learning Effort is supported by the logs. The student's reliance on the AI for debugging complex code (Log 03), saving time on repetitive operations, and getting help with tasks they have not done before demonstrates a clear dependency for efficiency and tackling novel problems. The nature of questions seeking guidance on fundamental architectural patterns like DAO implementation (Log 09), choices for database datatypes, and even the "best order to implement the code" indicates a reliance on the AI to structure their learning and development process, potentially reducing independent critical thinking and problem-solving effort that would otherwise be required.

4.2.2.4 Theme 4: Impact on Problem-Solving, Teamwork, and Communication Skills

The integration of ChatGPT into PBL environments appears to have significant implications for students' development of essential professional skills. This theme examines (RQ3: How does the integration of ChatGPT in PBL environments impact software engineering students' problem-solving, teamwork, and communication skills?) how participants' experiences with ChatGPT influenced their approaches to problem-solving, critical thinking, and collaborative work—skills that are fundamental to success in vocational contexts. The analysis revealed three distinct but interconnected sub-themes that provide insights into how AI tools might reshape skill development in educational settings.

4.2.2.4.1 Problem-Solving

Participants consistently highlighted ChatGPT's ability to enhance problem-solving processes, particularly in addressing programming challenges that would otherwise create significant barriers to progress. Many described how ChatGPT facilitated debugging processes and provided alternative approaches when they encountered obstacles.

A recurring pattern in the interviews was the use of ChatGPT to overcome specific technical challenges. Candidate-04 explained, "*Fixing my broken code was the biggest help. I'd send it back, explain the mistake in detail, and it would come back with better or correct code".* Similarly, Candidate-15 reported, "*In the JSP project, I had a bug in my code that I couldn't trace. I gave ChatGPT the code, and it pointed out exactly where the issue was".*

ChatGPT appeared to function as a scaffold for problem-solving, providing structured support that guided students through complex tasks. Candidate-06 contrasted traditional problem-solving approaches with ChatGPT-assisted methods: "*Before, I'd hit a problem, Google it, and spend days without a fix, feeling stuck and ready to give up. With ChatGPT, I ask directly, and it guides* *me step-by-step to the answer"*. This structured support aligns with findings from Hmelo-Silver et al. (2007), who note that effective scaffolding in problem-based learning provides just enough structure to prevent cognitive overload while allowing learners to engage with complex problems.

ChatGPT also appeared to enhance motivation by preventing prolonged periods of being "*stuck"*. Candidate-15 reported, "*When I hit a bug in the JSP project, getting a fast answer from ChatGPT kept me motivated to keep working".* This observation resonates with SRL theory, which emphasises how positive efficacy beliefs contribute to student persistence (Zimmerman 2002).

Several participants described how ChatGPT helped them overcome creative blocks and identify new approaches. Candidate-01 explained, *"We'd start with an idea, but sometimes we'd get stuck halfway and run out of inspiration".* In these situations, ChatGPT served as a catalyst for renewed problem-solving efforts.

4.2.2.4.2 Critical Thinking

While ChatGPT facilitated problem-solving, participants also described processes that required them to exercise critical thinking skills when evaluating and implementing AI-generated solutions. The research identified the development of verification habits as a significant aspect of critical engagement with AI tools.

Many participants described developing systematic approaches to verify ChatGPT's outputs. Candidate-06 explained, "*I usually take its answers and cross-check them. For data, I Google to see if similar info exists or ask it for academic sources to verify"*. Candidate-05 similarly noted, "*If ChatGPT's answer matches those, I trust it; if not, I check Google or YouTube tutorials. I learned to double-check"*.

Participants frequently discussed adapting and refining ChatGPT's suggestions rather than implementing them directly. Candidate-02 stated, "*I had to figure out where it went wrong, tweak the code, and keep refining it. That process of* *questioning and adjusting really sharpened my critical thinking".* Similarly, Candidate-07 explained, "*I tweaked its code to match my style, like adjusting a function's approach. That deepened my understanding of the material, not just helped me finish the project".*

Several participants emphasised that successful use of ChatGPT required pre-existing knowledge. Candidate-15 observed, "*I think even with ChatGPT, you need a base to use it well—it's not just handed to you",* while Candidate-16 noted, "*I think I learned, but you need a base to use it well—it's not just given to you".* This aligns with Vygotsky's (1981) zone of proximal development concept, suggesting that AI tools might be most effective when they build upon existing knowledge rather than attempting to replace foundational learning.

Some participants noted that formulating effective questions for ChatGPT itself required critical thinking. Candidate-01 observed that "*with ChatGPT, I have to think through my questions clearly first, which makes me more organised".* This metacognitive process of question formulation represents an important critical thinking skill that might be enhanced through AI interaction.

4.2.2.4.3 Teamwork and Communication

Participants reported complex and sometimes contradictory effects of ChatGPT on teamwork and communication patterns. While some described enhanced collaboration, others noted reduced interpersonal interaction and potential challenges for team coordination.

Several participants reported reduced team communication following ChatGPT adoption. Candidate-08 stated directly, "*It reduced communication with classmates",* elaborating that "*that cuts down on team interaction, and I don't always know what teammates are thinking".* Candidate-09 similarly noted, "*It cut down on team communication. Before, we'd work offline together on one computer. With ChatGPT, we'd share screens online—one person uses it while others do their own tasks, with less exchange".*

Some participants observed changing task division patterns within teams. Candidate-13 explained, "*Before ChatGPT, we had much clearer, more defined divisions of work, and each person's workload was way higher. With ChatGPT, what might've taken three people to code can now be done by one or two. The division isn't as extreme—it's less exaggerated".* This observation suggests AI tools might flatten traditional specialisation patterns in team settings.

Several participants noted that ChatGPT could foster more inclusive participation in technical tasks. Candidate-15 explained, "*In the JSP project, I could take on coding tasks I'd normally shy away from because ChatGPT provided guidance, spreading the load so everyone could pitch in more evenly"*. This suggests potential for AI tools to reduce skill barriers that might otherwise limit full participation in team projects.

Despite reduced communication in some contexts, several participants described using ChatGPT as a shared resource that facilitated decision-making. Candidate-06 explained, "*With ChatGPT, we can ask it for suggestions, like two tech options to choose from, and then discuss and decide. It's like a helper guiding our analysis, saving time and making choices clearer".* Similarly, Candidate-07 noted, "*When we disagree, we ask ChatGPT for pros and cons, which is less confrontational than arguing. It helps us pick a direction more clearly".*

Some participants found that ChatGPT use actually increased the importance of deliberate team coordination. Candidate-11 observed, "*After this project, I realised communication is key. ChatGPT might suggest one direction, but teammates might be on different ones. Even with its suggestions, you need to focus on aligning everyone to one approach since it's a single project"*.

4.2.2.4.4 Checking with the ChatGPT log for Theme 4

The log data offers examples illustrating the AI's contribution to problem-solving and fostering critical thinking. For Problem-Solving, students made remarks on log03 that explicitly credits the AI with resolving technical difficulties, stating, "*When executing complex SQL code, I tend to miss some double quotes and* *single quotes, resulting in SQL ERROR. GPT can easily solve these problems"* (Log 03). The logs show the AI providing detailed steps for configuring Git, and correcting database trigger logic. This highlights the AI's direct assistance in overcoming technical hurdles. For Critical Thinking, the AI encourages a structured approach to development by outlining project phases (Log 08), detailing necessary processes and data types, explaining architectural design principles (Log 02), and providing guidance on best practices for web design, error handling, and logging. The user's diverse questions, ranging from implementation details to architectural design (Log 09), suggest active intellectual engagement and the application of critical thought to the project's complexities. Furthermore, the AI acting as an "*outside reviewer"* and providing structured feedback on project criteria implicitly encourages the user to critically evaluate their work against defined standards (Lab 06).

On the other hand, the provided chat logs contain limited direct evidence regarding the impact on Teamwork and Communication amongst team members, although the project is noted as being undertaken by a group, and the AI provides guidance relevant to managing project tasks and interacting with stakeholders.

4.2.2.5 Theme 5: Implications for Vocational Education Curricula

Implications for vocational education curricula regarding the integration of AI tools like ChatGPT were identified through the analysis of interview data. This theme encapsulates how educational institutions might need to adapt their approaches to prepare students for an AI-augmented workplace while ensuring meaningful learning outcomes. Six distinct but interconnected sub-themes were identified from participants' responses, with respect to RQ 1.4 (What are the implications of integrating ChatGPT into PBL settings for the curricula in vocational education institutions in Hong Kong?).

4.2.2.5.1 Curriculum Integration and Adaptation

Participants overwhelmingly recommended integrating ChatGPT into formal curricula. Candidate-14 suggested "*integrating ChatGPT into PBL or other* *assignments"* and argued that "*schools should proactively integrate ChatGPT and teach correct use".* Candidate-03 endorsed this approach: "*I think it's a great idea. ChatGPT helps me learn the subject's content faster".*

Some participants called for fundamental curriculum revision. Candidate-16 argued, "*But the curriculum should shift too—focus on practical AI use instead of outdated methods"*, using the evocative metaphor: "*It's like using a ballpoint pen instead of a quill".* This suggests that curricula should not merely add AI tools as supplements but restructure to reflect technological realities.

Participants highlighted efficiency benefits of curriculum integration. Candidate-01 noted, "*It's efficient. It answers come fast, saving time for deeper learning",* suggesting that time saved through AI assistance could be redirected toward higher-order learning activities.

4.2.2.5.2 Workplace Readiness and Future Skills Development

Participants consistently highlighted the importance of AI literacy as a critical workplace skill. Several expressed concerns about students' competitive disadvantage if educational institutions fail to incorporate AI tools into learning environments. Candidate-09 directly stated, "*With AI growing fast, you'll use tools like ChatGPT at work. Learning it in school builds job competitiveness".* This sentiment was echoed by Candidate-15, who drew a compelling analogy: *"If you ban AI completely, they'll be at a disadvantage like using mental math while others use calculators".*

The interviews revealed a strong perception that PBL environments using AI tools closely simulate workplace scenarios. Candidate-15 noted, "*Project-based learning mimics those settings, so welcoming AI makes sense for future jobs",* and elaborated that *"in the JSP project, ChatGPT helped me contribute to coding tasks I wasn't strong in, preparing me for real-world scenarios where AI is common".*

Candidate-16 argued for urgency in curriculum adaptation: "*AI's the future, schools should teach students to use it sooner rather than later. Students need* *to understand how to wield it effectively to stay competitive".* This forward-looking perspective suggests vocational education must proactively prepare students for technological workplace evolution.

4.2.2.5.3 Personalised Learning Enhancement

Participants identified ChatGPT's potential to address learning barriers that traditional educational settings cannot always overcome. Candidate-04 highlighted the accessibility challenge in traditional classrooms: *"In class, with one teacher and lots of students, you don't always feel comfortable asking questions".* Candidate-08 praised ChatGPT's approachability: "*ChatGPT's perfect—no pressure, and it teaches even if you don't know the technical stuff".*

Several participants envisioned enhanced personalisation features. Candidate-12 suggested, *"It'd be great if it could give a learning plan when you ask a question"* and elaborated that "*a plan suggesting which concepts to learn for specific project tasks would've guided my self-learning better".* Building on this concept, Candidate-13 proposed more sophisticated personalisation: *"it could offer more personalised learning—like tailoring resources to a user's progress, making it easier and reminding them what to focus on".*

Participants also identified ChatGPT's potential to support project planning. Candidates 10 and 11 both mentioned that summarising complex requirements could enhance early project planning, with Candidate-11 noting, "*In the JSP project, the requirements were lengthy, and a clear summary early on would've saved us from messy revisions later".*

4.2.2.5.4 Pedagogical Strategies for Effective ChatGPT

Participants emphasised the need for specific pedagogical approaches to optimise ChatGPT's educational value. A recurring suggestion was teaching effective prompt engineering skills. Candidate-01 stated, "*teaching students how to ask better questions and follow up would make it more valuable for learning"*, while Candidate-08 simply urged educators to "*teach students how to communicate with ChatGPT"*.

Participants stressed that educators should frame AI as a complementary tool rather than a replacement for critical thinking. Candidate-13 noted, "*students need the mindset that's a tool, not a replacement for critical thinking",* while Candidate-14 suggested "*showing students how to use it as a tool rather than copying answers as their own".*

The research identified the importance of reflective engagement with AI-generated content across multiple interviews. Candidate-06 contrasted different approaches: "*If you just copy-paste code without analyzing, it can hurt your learning. But if you're curious and dig into what it says, it's better—you learn more"*. Candidate-05 succinctly captured this principle: "*It's a tool that supports learning, as long as you use it thoughtfully"*.

4.2.2.5.5 Enhanced Learning Outcomes Through ChatGPT

Participants reported that thoughtful ChatGPT use deepened their understanding of course material. Candidate-13 stated, "*It enhanced our learning and filled gaps, helping us understand the course material beyond just finishing the project".* Candidate-07 noted, "*It also teaches us more—class material plus extra insights".*

Many participants described how ChatGPT helped them grasp concepts they had struggled with in traditional instruction. Candidate-15 shared a specific example: "*in the JSP project, it helped me understand server connections better by explaining concepts I'd only partially grasped in class. That knowledge stuck with me, so I learned the material, not just finished the project".*

The research identified a key distinction between using ChatGPT merely to complete assignments versus using it to enhance understanding. Candidate-01 articulated this difference: "*If you're not just asking ChatGPT for exam answers to memorize, but actually understanding its explanations, you're learning".* Candidate-16 reinforced this perspective: "*I didn't just rely on it to finish—I used it to deepen my knowledge, so I learned the material, not just completed the project".*

4.2.2.5.6 Balancing AI Assistance with Independent Thinking

Participants expressed concerns about maintaining critical thinking skills alongside AI adoption. Candidate-01 recommended that ChatGPT *"should encourage critical thinking more"* and suggested it "*could guide us to think by asking counter-questions or offering different angles".* They cautioned, "*we can't over-rely on it. We need to keep thinking and collaborating, not just copy its answers"*.

Some participants noted potential negative impacts on collaborative learning. Candidate-08 observed that ChatGPT use "*cuts down on team interaction, and I don't always know what teammates are thinking"*, suggesting educators should consider how AI tools might affect group dynamics.

Participants emphasised that outcomes depend significantly on how students approach the technology. Candidate-13 observed: "*It's about using it wisely—some excel with it, others misuse it and struggle. It depends on how you approach it".* Candidate-12 cautioned against uncritical use: "*But for reports, schools should watch out—it's too convenient, and students might just dump everything in there".*

4.2.2.5.7 Checking with the ChatGPT log for Theme 5

The conversation logs between the user and ChatGPT during the development of a centralised equipment management system highlight AI's transformative potential in vocational education, particularly in software engineering. AI's ability to provide instant technical support, debug code, suggest design patterns, and structure complex tasks (Log 05) underscores its role in enhancing workplace readiness and personalised learning. For instance, the user notes, "*When executing complex SQL code, I tend to miss some double quotes and single quotes, resulting in SQL ERROR. GPT can easily solve these problems"* (Log 03), illustrating AI's capacity to remove technical barriers and improve problem-solving. Additionally, AI's guidance on UI design, database schemas, and project management (Logs 02, 04) supports teaching practical skills, while its role as an "outside reviewer" (Log 06) aids self-assessment. However, curricula must balance AI use with independent thinking to ensure students develop critical skills without over-reliance, necessitating pedagogical strategies for effective AI integration.

4.2.3 Summary of Qualitative Findings

The thematic analysis addresses the research question and its sub-questions (RQs 1.1–1.4), and the findings complement quantitative data detailed in Section 4.1. The summary of qualitative findings is presented in Table 4.9.

Theme	Sub-Theme	Characteristics
Theme 1: ChatGPT's Role in Supporting SRL Components	Control of Learning Belief	Students viewed ChatGPT as a supportive tool, not a replacement, fostering autonomy, responsibility, and a growth mindset.
	Metacognitive Self-Regulation	Supported planning (breaking down tasks), monitoring (identifying knowledge gaps), and evaluation (self-testing, verification habits).
	Self-Efficacy	Boosted confidence, reduced anxiety when tackling complex tasks, and provided quick solutions increasing persistence.
	Help-seeking Behaviour	Lowered psychological barriers; allowed asking "simple/silly" questions without judgment, and provided always-available support.
	Time and Study Environment Management	Provided time efficiency; instant answers saved effort in routine tasks; enabled focus on higher-value learning.
Theme 2: Perceived Benefits of ChatGPT in PBL	Personalised Guidance and Step-by-step Explanations	Individualised, adaptive explanations, and sequential breakdown of problems.
	Enhanced Comprehension and Information Management	Simplified difficult concepts; integrated information from multiple sources.
	Always-Available Learning Support	24/7 accessibility; immediate help overcame delays and anxiety.
	Enhanced Creativity and Idea Generation	Sparked creativity; offered alternative approaches; expanded perspectives.

	Debugging and Error Resolution Support	Aided in bug fixing with explanations; educational scaffolding for coding tasks.
	Time Efficiency and Streamlined Learning	Reduced search time, and faster completion of tasks enabled focus on complex/creative work.
Theme 3: Challenges and Limitations of ChatGPT Integration	Technical Limitation in Complex Task Management	Struggled with large projects, losing context, or handling extensive codebases; required breaking tasks into pieces.
	Verification Requirements and Accuracy Concerns	Responses not always accurate; hallucinations/fabricated information; required cross-checking.
	Risk of Dependency and Reduced Learning Effort	Over-reliance reduced independent problem-solving; potential academic integrity risks.
Theme 4: Impact on Problem-Solving, Teamwork, and Communication Skills	Problem-Solving	Enabled debugging, alternative approaches, and reduced time "being stuck"; functioned as problem-solving scaffold.
	Critical Thinking	Encouraged verification, refinement, and evaluation of AI outputs; effective prompting required critical engagement.
	Teamwork and Communication	Mixed effects: sometimes reduced collaboration but also broadened participation and aided team decision-making.
Theme 5: Implications for Vocational Education Curricula	Curriculum Integration and Adaptation	Students urged formal integration; curricula should evolve to reflect AI-driven practices.
	Workplace Readiness and Future Skills Development	AI literacy framed as essential for employability and competitiveness.
	Personalised Learning Enhancement	Proposed GPT-generated study plans and tailored resources; supported project planning.
	Pedagogical Strategies for Effective ChatGPT	Need for training in prompt engineering; AI framed as complement, not replacement.
	Enhanced Learning Outcomes Through ChatGPT	Deepened understanding of course content; enabled learning beyond project completion.
	Balancing AI Assistance with Independent Thinking	Caution against over-reliance; stressed role of critical thinking and collaboration alongside AI use.

Table 4.9 Theme Summary Table

ChatGPT enhanced SRL components, including control of learning belief, metacognitive self-regulation, self-efficacy, help-seeking, and time management (Pintrich, 2000; Zimmerman, 2002). Students reported greater autonomy, with one stating, "*I saw it as a tool, not something to fully rely on—I'd still think for myself and not trust its answers 100%*". Logs showed planning through architectural design queries (Log 04), monitoring via error resolution, and evaluation by requesting ChatGPT as an "outside reviewer" (Log 06). Help-seeking was frequent, and efficiency was noted: *"In some repetitive operations, GPT can help me save time"*.

Students perceived ChatGPT as a versatile tool, offering tailored guidance, enhanced comprehension, constant availability, creativity, debugging, and time efficiency. UI design suggestions and Chart.js recommendations exemplified personalised and creative support. The user noted, "*When executing complex SQL code, I tend to miss some double quotes and single quotes, resulting in SQL ERROR. GPT can easily solve these problems*", highlighting debugging and efficiency (Hmelo-Silver, 2004).

Challenges included technical limitations, accuracy concerns, and dependency risks. While logs showed ChatGPT handling complex tasks like Git configuration, verification was essential, as students cross-checked outputs. Dependency was evident in the user's reliance on ChatGPT for debugging and task structuring, potentially reducing independent problem-solving.

ChatGPT improved problem-solving by aiding debugging (Log 03) and fostered critical thinking through verification and question formulation. But teamwork effects were mixed, with reduced interaction for some but inclusive participation for others (Log 06). Architectural design queries reflected critical engagement (Vygotsky, 1981).

Curricular integration of ChatGPT was recommended to enhance workplace readiness and personalised learning. Students advocated teaching prompt engineering and framing AI as a complementary tool (Candidate-13). The user's reliance on ChatGPT for technical support (Log 05) and self-assessment

(Log 06) underscored its potential, but balancing AI use with independent thinking was critical to avoid over-reliance (Hmelo-Silver et al., 2007; Zimmerman, 2002).

4.3 Integrated Discussion

Conversational AI, like ChatGPT, offers a promising intervention by providing personalised, scalable assistance that can address challenges such as resource constraints and robust student support. Specifically, ChatGPT can intervene in PBL by facilitating key SRL components—such as planning, monitoring, and help-seeking—through tailored guidance, immediate feedback, and 24/7 availability. This study's findings, drawn from quantitative (MSLQ scores, assessments, usage logs) and qualitative (interviews, ChatGPT logs) data, illuminate how ChatGPT enhances SRL within PBL, offering insights into its benefits, limitations, and implications for vocational education curricula. The discussion integrates these findings to explore ChatGPT's role in supporting SRL and optimising PBL implementation.

4.3.1 Overall Impact on SRL in PBL Settings Using Conversational AI for VPET (Main RQ)

The integration of ChatGPT into PBL environments at V-Institute has shown a comparable, and in aspects of Effort Regulation and Help Seeking marginally enhanced, ability to foster SRL among software engineering students compared to traditional human-facilitated PBL. This section addresses the main research question (RQ: How does the use of ChatGPT in project-based learning impact software engineering students' self-regulated learning?) by synthesising quantitative and qualitative findings, aligning PBL components with SRL phases, assessing academic performance, and exploring implications for VPET in software engineering.

4.3.1.1 SRL Support in PBL with ChatGPT versus Traditional PBL

Quantitative results from the MSLQ indicated significant SRL improvements in both the experimental (n=42, PBL with ChatGPT) and control groups (n=42, traditional PBL) from pre-test to post-test ($p<0.001$, effect sizes $d=0.225$–0.965). The experimental group demonstrated significant advantages in Effort Regulation and Help-Seeking ($p<0.05$), suggesting ChatGPT enhances specific SRL behaviours critical for VPET's focus on practical, industry-aligned skills (Vocational Training Council, 2020a). Qualitative data reinforced this, with students viewing ChatGPT as a "*tool, not a replacement for critical thinking*", promoting autonomy similar to human facilitators but with greater accessibility. The experimental group's frequent ChatGPT use (18.5 sessions/week, lasting some 222 minutes) compared to the control group's 38-minute enquiry sessions highlights its role in enabling spontaneous SRL engagement, aligning with Zimmerman's (2002) emphasis on proactive learning. In VPET, where software engineering demands rapid adaptation to technological advancements, ChatGPT's 24/7 availability addresses resource constraints, as Candidate-05 noted: *"I didn't have to wait until the next class to continue".*

4.3.1.2 Student Academic Performance

Academic performance data showed a modest advantage for the experimental group, with significantly higher final scores ($M=60.3$ vs. 55.8, $p=0.041$, $d=0.460$) but no significant differences in test ($p=0.103$) or project scores ($p=0.064$). Lower score variability in the experimental group (e.g., test $SD=13.3$ versus 21.6) suggests consistent performance, likely due to ChatGPT's scaffolding capability, which depends on a student's prompt. Candidate-15 highlighted this: "*Quick bug fixes made the project feel less overwhelming*", enabling a focus on advanced tasks. However, the lack of significant project score differences indicates ChatGPT complements rather than transforms PBL's deep learning outcomes, aligning with Blumenfeld et al. (1991). For VPET, this consistency supports software engineering students in meeting industry standards reliably.

4.3.1.3 Relevance to VPET in Software Engineering

In VPET, software engineering education prioritises practical skills and workplace readiness (HKSAR Education Bureau, 2020). ChatGPT's integration addresses VPET challenges, such as limited instructor availability and external mentor access (Aldabbus, 2018), by providing scalable, personalised support. Its ability to foster help-seeking (Candidate-07: *"I can ask without feeling awkward*") and enhance efficiency aligns with VPET's emphasis on preparing students for fast-paced technology environments. However, challenges like dependency risks and accuracy concerns (Candidate-06: "*I cross-check with reliable sites*") necessitate VPET curricula that teach critical AI engagement. Mixed teamwork impacts like reduced communication (Candidate-08), but inclusive participation (Candidate-15) suggests VPET must balance AI use with collaborative skills training. By embedding prompt engineering and reflective practices, VPET can leverage ChatGPT to enhance SRL while ensuring students develop independent problem-solving skills essential for software engineering careers.

4.3.2 Enhancing SRL through Conversational AI in PBL (RQ 1.1)

This section addresses RQ1.1: How can ChatGPT be integrated into Project-Based Learning (PBL) environments to support the development of the key components of SRL among software engineering students in vocational education? Drawing on quantitative and qualitative findings from the study, it examines how ChatGPT can be embedded within PBL to enhance SRL components—control of learning belief, metacognitive self-regulation, self-efficacy, help-seeking, and time and study environment management. The discussion is organised by SRL phases (forethought, performance, self-reflection), mapping PBL components and ChatGPT interventions, and aligning with VPET's software engineering goals, omitting perceived benefits, challenges, and practical implications as these are addressed elsewhere. Figure 4.3 illustrates how ChatGPT supports PBL activities to foster students' SRL across the forethought, performance, and self-reflection phases, depicting the alignment of AI interventions with SRL components in the context of software engineering projects (Zimmerman, 2002).

4.3.2.1 Integration by SRL Phases, PBL Components, and ChatGPT Interventions

Quantitative data from the MSLQ showed significant SRL improvements for both the experimental group (n=42, PBL with ChatGPT) and control group (n=42, traditional PBL) from pre-test to post-test ($p<0.001$, effect sizes $d=0.225–0.965$), with the experimental group excelling in Effort Regulation and Help-Seeking ($p<0.05$). Qualitative insights from interviews and ChatGPT logs (Log 01–10) illustrate how ChatGPT supports SRL within PBL's framework (Gao & Yang, 2023), tailored to VPET's focus on practical skills.

1. **Forethought Phase (Goal Setting and Planning)**

PBL Components: Student-centric learning and inquiry-based learning encourage students to set project goals and plan tasks, fostering control of learning belief and metacognitive self-regulation (Gao & Yang, 2023).

ChatGPT Interventions: ChatGPT can be integrated to generate project outlines and clarify requirements, enhancing autonomy and planning. Candidate-02 noted, "*It broke the project down into clear steps*", while logs showed queries for architectural designs (Log 04). Educators can embed ChatGPT to create work breakdown structures, aligning with VPET's emphasis on independent project management in software engineering (Vocational Training Council, 2020b).

SRL Components Supported: Control of learning belief, as students view ChatGPT as "*a tool, not something to fully rely on*" (Candidate-09), and metacognitive self-regulation through structured planning.

2. **Performance Phase (Monitoring and Control)**

PBL Components: Collaborative and authentic tasks require active monitoring and help-seeking, supporting metacognitive self-regulation, self-efficacy, and help-seeking (Zimmerman, 2002).

ChatGPT Interventions: ChatGPT facilitates real-time debugging and concept clarification, enhancing monitoring and confidence. Candidate-01 reported, "*It pointed out gaps in my understanding*", and logs showed error resolutions (Log 05: HTTP 404). Integration involves using ChatGPT for debugging or querying concepts, as Candidate-07 noted: "*I can ask simple questions without judgment*". This supports VPET's practical problem-solving focus (Newman, 2002).

SRL Components Supported: Metacognitive self-regulation (monitoring), self-efficacy (Candidate-15: "*Issues felt less overwhelming*"), and help-seeking via continuous assistance (Log 08).

3. Self-Reflection Phase (Evaluation and Reflection)

PBL Components: Reflective practices in PBL foster evaluation, supporting metacognitive self-regulation and self-efficacy (Gao & Yang, 2023).

ChatGPT Interventions: ChatGPT can act as an "*outside reviewer*" (Log 06), prompting students to assess project outcomes. Candidate-11 stated, "*It pushed me to research further".* Integration includes using ChatGPT to generate practice questions or review project criteria, as Candidate-14 described: "*It quizzed me, making learning interactive*". This enhances metacognition, crucial for VPET's lifelong learning goals in software engineering (HKSAR Education Bureau, 2020).

SRL Components Supported: Metacognitive self-regulation (evaluation) and self-efficacy through reflective feedback.

(Cross-Phase Support) Time and Study Environment Management

PBL Components: Authentic tasks in PBL require efficient resource management, supporting time and study environment management (P. R. Pintrich, 2000).

ChatGPT Interventions: ChatGPT streamlines routine tasks, enabling a focus on complex project aspects. Candidate-16 noted, "*Tasks that took four hours* *were done in one*", with logs highlighting efficiency in repetitive operations (Log 03). Educators can integrate ChatGPT for quick resource access or error fixes, creating productive study environments aligned with VPET's fast-paced training needs.

SRL Component Supported: Time and study environment management, enhancing efficiency across all SRL phases.

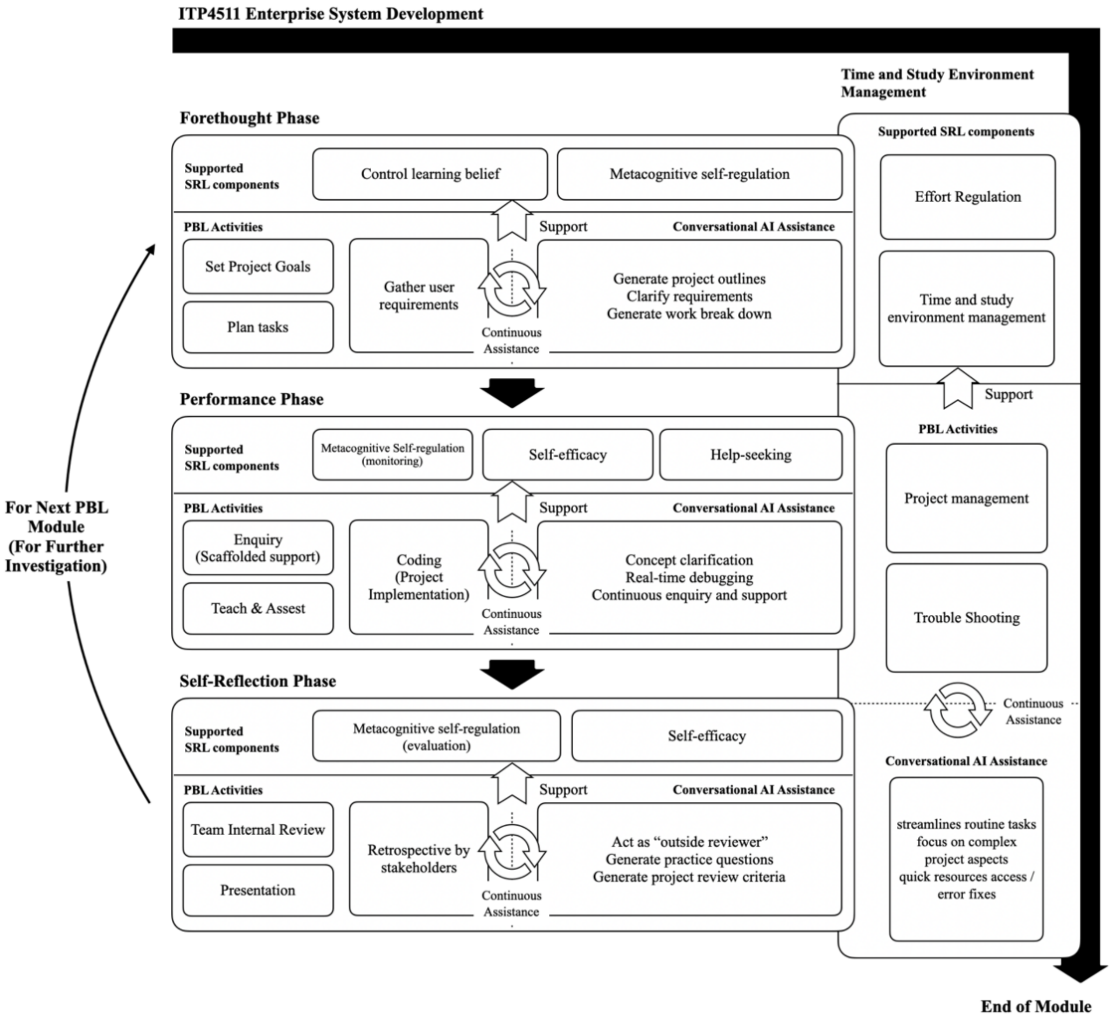


Figure 4.3 How ChatGPT assists PBL activities and supports SRL

4.3.2.2 Alignment with VPET in Software Engineering

VPET prioritises practical skills and workplace readiness in software engineering (HKSAR Education Bureau, 2020). ChatGPT's integration into PBL supports SRL by providing scalable tools for planning, debugging, and reflection, addressing resource constraints like limited instructor availability (Vocational Training Council, 2020b). These interventions prepare students for software engineering's dynamic demands, fostering autonomous, industry-ready professionals.

4.3.3 Perceived Benefits and Challenges (RQ1.2)

This subsection addresses RQ1.2: What are the perceived benefits and challenges of using ChatGPT in PBL settings for software engineering students? It synthesises qualitative findings from semi-structured interviews and ChatGPT conversation logs (Logs 01–10). The discussion is divided into two parts: the perceived benefits, and challenges and limitations. These subsections highlight how ChatGPT influences PBL and SRL for software engineering students, with implications for VPET's industry-aligned education.

4.3.3.1 Perceived Benefits

Qualitative data revealed six key benefits of integrating ChatGPT into PBL, enhancing SRL and aligning with VPET's focus on practical skills and workplace readiness (HKSAR Education Bureau, 2020). First, personalised guidance and step-by-step explanations enabled tailored support, as Candidate-03 noted: "*ChatGPT guided me through each step until I could solve it myself*". Logs showed detailed UI design suggestions (Log 04), scaffolding learning within students' zones of proximal development (Hmelo-Silver, 2004). Second, enhanced comprehension and information management simplified complex concepts, with Candidate-06 stating: "*It presents complex topics in an easier way*". Logs demonstrated synthesis of project requirements (Log 02) aiding knowledge integration critical for software engineering tasks.

Third, always-available learning support addressed VPET's resource constraints, offering 24/7 assistance. Candidate-07 valued: "*I could work late and still get answers*", reducing delays in project progress (Zimmerman, 2002). Fourth, enhanced creativity and idea generation sparked innovation, as Candidate-01 explained: "*It sparked creativity and helped us analyze problems* *from new angles*". Logs showed suggestions like Chart.js for data visualisation (Log 06), enriching project outcomes. Fifth, debugging and error resolution support was pivotal, with Candidate-15 reporting: "*It pointed out exactly where the issue was*". Log 03 highlighted SQL error fixes, streamlining technical tasks. Finally, time efficiency and streamlined learning allowed focus on higher-order tasks, as Candidate-16 noted: "*Tasks that took four hours were done in one*". Logs confirmed efficiency in repetitive operations (Log 03), aligning with VPET's fast-paced training needs (Vocational Training Council, 2020a).

These benefits collectively enhanced SRL by fostering autonomy, metacognition, and self-efficacy, enabling students to manage complex software engineering projects effectively. For instructors, ChatGPT reduced workload by handling routine queries, supporting VPET's scalable education model.

4.3.3.2 Challenges and Limitations

Despite its benefits, three primary challenges were identified. First, technical limitations in complex task management hindered ChatGPT's ability to handle large codebases or maintain context. Candidate-11 noted: "*It can't handle big projects well*", and logs showed occasional context lapses (Log 05), requiring manual input segmentation. This limits its utility in advanced software engineering projects, necessitating supplementary tools or instructor support. Second, verification requirements and accuracy concerns were significant, as Candidate-14 warned: "*It can hallucinate—making up stuff that doesn't exist".* Students spent time cross-checking outputs (Candidate-06: "*I check with reliable sites*"), with logs indicating manual verification of SQL code (Log 03). This underscores the need for critical engagement, aligning with VPET's emphasis on independent problem-solving (Gao & Yang, 2023).

Third, risk of dependency and reduced learning effort posed concerns, with Candidate-04 admitting: "*I rely on it too much, so I feel lazy*". Logs showed reliance on ChatGPT for debugging and task structuring (Log 08), potentially undermining deep learning. For instructors, this raises issues of academic integrity, as Candidate-12 cautioned: *"Students might just dump everything in there".* In VPET, where software engineering demands robust critical thinking, over-reliance could hinder students' readiness for industry challenges (Hmelo-Silver et al., 2007).

4.3.4 Impact on Problem-Solving, Teamwork and Communication Skills (RQ 1.3)

This subsection addresses RQ1.3: How does the integration of ChatGPT in Project-Based Learning (PBL) environments impact software engineering students' problem-solving, teamwork, and communication skills? Using qualitative data from interviews and ChatGPT logs (Log 01–10), it explores these impacts, supplemented by quantitative insights. The discussion aligns with VPET's focus on industry-ready software engineering skills (HKSAR Education Bureau, 2020).

4.3.4.1 Problem-Solving Skills

ChatGPT bolstered problem-solving by offering rapid technical solutions, with Candidate-04 noting: *"It fixed my broken code effectively"*. Logs showed resolutions for SQL and HTTP 404 errors (Log 03, Log 05). Quantitative data indicated consistent performance in the experimental group (n=42, test SD=13.3 versus control SD=21.6), suggesting ChatGPT's scaffolding stabilised outcomes (Blumenfeld et al., 1991). This supports VPET's need for iterative problem-solving in software engineering (Vocational Training Council, 2020b).

4.3.4.2 Critical Thinking Ability

Critical thinking, integral to problem-solving, was enhanced as students verified ChatGPT's outputs. Candidate-06 said: "*I cross-check with reliable sites*", with logs showing code refinements (Log 05). Formulating precise prompts also sharpened metacognition, as Candidate-01 observed: "*I think through questions clearly*". This aligns with Vygotsky's (1981) concept of tools building on existing knowledge, fostering VPET's emphasis on independent analysis (Gao & Yang, 2023).

4.3.4.3 Impacts on Teamwork

ChatGPT's impact on teamwork was mixed. It reduced interaction for some, with Candidate-08 reporting: "*It cut down team interaction*". Logs showed individual debugging queries (Log 08). However, it enabled inclusive participation, as Candidate-15 noted: "*I took on coding tasks I'd avoid*". Group queries for project options (Log 06) aided decision-making. Quantitative data showed no significant project score differences (p=0.064), suggesting comparable collaboration outcomes. VPET curricula must reinforce teamwork to counterbalance AI-driven independence.

4.3.4.4 Impacts on Communication

Communication effects were nuanced. Reduced interaction limited verbal practice, per Candidate-09: "*Less exchange*". Yet, ChatGPT mediated disputes, with Candidate-07 stating: "*It's less confrontational for pros and cons*". Logs showed technical option queries (Log 06), clarifying discussions. Some prompt formulation improved articulation, supporting VPET's need for effective team communication (Zimmerman, 2002). Structured AI use can enhance this skill.

4.3.5 Practical Implications (RQ 1.4)

This subsection addresses RQ1.4: What are the implications of integrating ChatGPT into PBL settings for the curricula in vocational education institutions in Hong Kong? Drawing on qualitative findings from interviews and ChatGPT logs (Log 01–10) collected, the discussion emphasises curriculum redesign, teaching strategies, and alignment with VPET's industry-focused objectives, avoiding overlap with prior sections on benefits, challenges, and skill impacts (HKSAR Education Bureau, 2020).

4.3.5.1 Curriculum Redesign for AI Integration

To leverage ChatGPT, VPET curricula should incorporate AI-driven PBL activities within software engineering modules, such as system design or coding projects. Candidate-14 urged: "*Integrate ChatGPT proactively into* *assignments*". Logs showed its use in generating project frameworks (Log 02), suggesting curricula should formalise such applications to enhance SRL. Redesigning learning outcomes to include AI tool proficiency ensures students master industry-relevant skills, aligning with VPET's goal of producing technological-savvy professionals (Vocational Training Council, 2020b). For instance, modules could require students to use ChatGPT for iterative design reviews, fostering autonomy and practical expertise.

4.3.5.2 Teaching Strategies to Optimise AI Use

Effective pedagogy is crucial for ChatGPT integration. Candidate-01 highlighted: *"Teach students how to ask better questions*", underscoring the need for prompt engineering training. Logs revealed inconsistent query effectiveness (Log 08), indicating curricula should include workshops on crafting precise prompts to maximise AI utility. Educators should position ChatGPT as a supportive tool, as Candidate-13 emphasised: "*It's not a replacement for critical thinking*". Structured PBL tasks, such as using ChatGPT to simulate stakeholder feedback (Log 06), can promote reflective learning while preserving analytical skills, aligning with VPET's focus on critical thinking (Hmelo-Silver et al., 2007).

4.3.5.3 Fostering Industry-Relevant Competencies

ChatGPT's integration equips students for AI-augmented software engineering roles, a key VPET priority. Candidate-09 noted: "*Learning it builds job competitiveness".* Logs showed support for tasks like system configuration (Log 05), mirroring workplace practices. Curricula should introduce AI-assisted simulations, such as developing software prototypes with ChatGPT's input, to bridge academic and professional contexts. This prepares students for dynamic industry demands, fostering adaptability and technical proficiency (Gao & Yang, 2023) .

4.3.5.4 Promoting Balanced Skill Development

To ensure holistic skill growth, curricula must mitigate over-reliance on AI. Candidate-01 suggested ChatGPT "*encourage critical thinking by asking counter-questions*". Logs indicated potential dependency in routine tasks (Log 03). PBL tasks should require students to validate AI outputs, fostering independent analysis. Collaborative projects where ChatGPT supports group planning but not execution can maintain teamwork skills, essential for VPET's software engineering focus (Zimmerman, 2002). This balance ensures students develop both AI proficiency and traditional competencies.

4.4 Chapter Summary

This chapter synthesised findings from the study. Quantitative findings from the MSLQ and assessments show significant SRL improvements, with ChatGPT users excelling in effort regulation and help-seeking, and achieving modestly higher, more consistent academic scores. Qualitative insights from interviews and ChatGPT logs highlight enhanced autonomy, problem-solving, and efficiency, though challenges include technical limitations, accuracy concerns, and dependency risks. Critical thinking is fostered through output verification, but teamwork effects are mixed, necessitating structured integration to maintain collaboration. Curricular implications include embedding AI-driven PBL, teaching prompt engineering, and balancing AI use with independent thinking to ensure workplace readiness. These findings advocate for ChatGPT's role in VPET, enhancing scalable, practical education while addressing potential pitfalls to prepare students for software engineering careers.

Chapter 5: Conclusion, Implications and Reflections

This chapter consolidates the findings from the study at V-Institute, exploring ChatGPT's integration into PBL to enhance SRL among software engineering students in VPET. It is structured into four subsections: Section 5.1 summarises key findings, highlighting ChatGPT's impact on SRL and academic outcomes; Section 5.2 provides direct answers to the research questions, linking findings to the study's hypotheses; Section 5.3 examines implications for theory and practice, enriching educational technology discourse; Section 5.4 addresses limitations and proposes future research; and Section 5.5 offers reflections on the research journey and a concluding synthesis, providing recommendations for VPET.

5.1 Summary of Key Findings

This study combined data from the MSLQ and academic assessments with insights from interviews and ChatGPT logs to explore its impact on SRL, academic performance, and essential skills in a VPET context. ChatGPT enhances SRL in PBL settings, provides modest academic improvements, ensures consistent performance, and boosts problem-solving and critical thinking, though its benefits require critical engagement and structured integration to address challenges.

Impact on SRL: ChatGPT demonstrably supports self-regulated learning (SRL) in PBL settings, showing comparable results to traditional methods. It fosters key SRL components across Zimmerman's cyclical model, boosting student autonomy via improved effort regulation and help-seeking behaviours. Participants viewed ChatGPT as a facilitator, not a replacement for independent thinking, aligning with VPET's goal of developing adaptable, self-directed professionals. It enhances forethought through planning support, performance via real-time monitoring, and self-reflection as an "outside reviewer", promoting autonomous learners overall.

Academic Performance: The group using ChatGPT showed slightly higher academic outcomes (a higher mean score) and more consistent results (a lower SD value) than the traditional PBL group. Students noted that ChatGPT simplified tasks, allowing focus on advanced project elements, supporting VPET's goal of producing industry-ready graduates.

Benefits and Challenges: ChatGPT offered personalised guidance, creative suggestions, and efficient debugging, enhancing project quality. However, technical limitations, accuracy issues, and risks of over-reliance required users to critically evaluate its outputs, reinforcing VPET's emphasis on independent problem-solving.

Problem-Solving, Teamwork, Communication: ChatGPT strengthened problem-solving by providing quick technical solutions and encouraging critical verification habits. Its impact on teamwork was mixed, reducing interactions for some while enabling inclusive participation for others, highlighting the need for strategic integration to maintain collaborative skills essential for software engineering.

Curricular Implications: The findings recommend adapting VPET curricula for ChatGPT integration by embedding AI literacy and prompt engineering training, fostering effective use and awareness of limitations. Redesign of assessments should focus on problem-solving processes over outcomes, addressing integrity issues. Implementing structured collaboration, viewing ChatGPT as a team tool, can preserve teamwork skills. Clear AI usage guidelines to balance AI assistance with independent thinking should be provided. These changes prepare graduates for AI-enhanced workplaces while upholding critical thinking and collaboration vital for software engineering.

5.2 Answers to Research Questions

This section addresses the main research question and its four sub-questions. Each response draws on the quantitative and qualitative data to evaluate the corresponding hypotheses, providing evidence-based insights.

Main RQ: How does the use of ChatGPT in project-based learning impact software engineering students' self-regulated learning?

ChatGPT effectively supports self-regulated learning (SRL) in problem-based learning (PBL) settings, showing comparable results to traditional methods. It fosters key SRL components across Zimmerman's cyclical model (2002), enhancing student autonomy through improved effort regulation and help-seeking behaviours ($p<0.05$). Participants viewed ChatGPT as a facilitator, not a replacement for independent thinking, aligning with VPET's focus on adaptable, self-directed professionals. It bolsters forethought via structured planning, performance through real-time monitoring, and self-reflection as an "outside reviewer". This holistic support develops autonomous learners, yielding modest academic gains ($p=0.041$).

RQ 1.1: How can ChatGPT be integrated into project-based learning environments to support the development of the key components of self-regulated learning among software engineering students in vocational education?

ChatGPT can be integrated as a supportive tool in PBL, offering personalised guidance, real-time feedback, and reflective prompts that align with Zimmerman's (2002) SRL phases. It aids forethought through goal-setting and planning suggestions, performance via self-monitoring with debugging and progress checks, and reflection as an external reviewer for self-evaluation. Hypothesis 1.1 is supported: ChatGPT enhances students' goal-setting and self-monitoring comparably or better than traditional methods. MSLQ scores reflect comparable or slightly improved SRL outcomes, with statistics (p-values, Cohen's d) showing gains in effort regulation and help-seeking, promoting personalised learning.

RQ 1.2: What are the perceived benefits and challenges of using ChatGPT in PBL settings for software engineering students?

Perceived benefits include personalised guidance, creative suggestions, efficient debugging, and enhanced access to information, which improved problem-solving and project quality. Challenges encompass technical limitations (e.g., accuracy issues), risks of over-reliance leading to dependency, and potential for reduced independent thinking. Hypothesis 1.2, that students will report a range of perceived benefits from using ChatGPT, including improved access to information and enhanced problem-solving capabilities, is confirmed, but challenges such as reliance on AI for answers may also be identified.

RQ 1.3: How does the integration of ChatGPT in PBL environments impact software engineering students' problem-solving, teamwork, and communication skills?

ChatGPT integration positively impacts problem-solving by providing quick technical solutions and encouraging critical verification, resulting in more sophisticated projects. Teamwork shows mixed effects: reduced direct interactions for some, but increased inclusive participation for others including shy students. Communication skills improve indirectly through clearer idea articulation via AI prompts. Hypothesis 1.3, that ChatGPT users exhibit better problem-solving and collaboration than non-users, is partially supported.

RQ 1.4: What are the implications of integrating ChatGPT into PBL settings for the curricula in vocational education institutions in Hong Kong?

Implications include the need for curriculum adaptations such as embedding AI literacy, prompt engineering training, and redesigned assessments focusing on processes over outcomes to address integrity concerns. Structured frameworks could position ChatGPT as a team resource, preserving collaboration while preparing students for AI-augmented workplaces. Hypothesis 1.4, that the integration of ChatGPT into curricula will lead to positive changes in instructional practices, including increased use of technology-enhanced learning methods, is upheld.

5.3 Implications for Theory and Practice

The integration of ChatGPT into PBL environments provides significant theoretical contributions to the fields of SRL, PBL, and educational technology, particularly within the VPET context. These contributions enrich existing frameworks by demonstrating how Conversational AI can mediate learning processes, extending traditional models to incorporate technology-driven autonomy and metacognition.

5.3.1 Theoretical Implications

5.3.1.1 Advancing SRL Frameworks

This study extends Zimmerman's (2002) SRL model—forethought, performance, and self-reflection phases—by showing ChatGPT's facilitation of each. Quantitative MSLQ data revealed significant SRL gains ($p<0.001$, $d=0.225–0.965$), particularly in effort regulation and help-seeking ($p<0.05$), indicating enhanced self-regulatory processes. Qualitative insights, like Candidate-02's observation that ChatGPT "broke the project down into clear steps" (Log 04), underscore support for goal setting in forethought; real-time debugging (Log 05) aided performance monitoring; and "outside reviewer" role (Log 06) promoted reflection. Aligning with Pintrich's (2000) metacognitive focus, it expands SRL theory via AI scaffolding, positioning AI as a dynamic partner augmenting cognitive capacities—a novel vocational education contribution.

5.3.1.2 Enriching PBL Theory

This research advances PBL theory by showing AI integration's alignment with core elements: student-centric learning, inquiry-based approaches, collaboration, authenticity, and reflection (Gao & Yang, 2023). ChatGPT's personalised guidance and 24/7 availability (e.g., Candidate-07: "I could work late and get answers") boosted student agency and inquiry, echoing constructivist principles from Dewey (1938) and Vygotsky (1981). It supported authentic tasks like complex software projects (Log 06), linking theory to practice—a PBL key (Blumenfeld et al., 1991). Collaboration had mixed effects: reduced interaction for some (Candidate-08) but increased for others (Candidate-15), urging PBL framework refinements for AI's group dynamics impact and enriching technology-mediated collaboration discussions in vocational education.

5.3.1.3 Contributing to Educational Technology Discourse

The study enriches educational technology discourse by positioning ChatGPT as a transformative tool in VPET, enabling interactive, on-demand and personalised learning support. Unlike traditional technologies like calculators or the internet (Brynjolfsson & McAfee, 2014), ChatGPT's conversational capabilities enable adaptive, personalised learning, as seen in its tailored debugging support (Log 03). This aligns with Selwyn's (2019) call for technologies that augment rather than replace human learning, offering a theoretical lens for understanding AI's role in fostering critical thinking and autonomy. The necessity for students to verify AI outputs (Candidate-06: "*I cross-check with reliable sites*") reinforces the importance of the dimension to technology integration theories, emphasising critical engagement as a core competency in AI-augmented education especially with the Conversational AI powered by LLM.

5.3.1.4 Contextualising VPET

By situating the research within VPET, the study contributes to theoretical frameworks specific to vocational education, where practical skills and workplace readiness are paramount (HKSAR Education Bureau, 2020). ChatGPT's ability to simulate workplace tasks, such as system configuration (Log 05), aligns with PBL's authentic nature, reinforcing VPET's applied learning goals. This contextualisation highlights AI's potential to address resource constraints, a persistent challenge in vocational settings (Aldabbus, 2018) and extends theoretical discussions on aligning technology with industry demands.

5.3.2 Practical Implications

The practical implications of this study provide actionable strategies for educators, policymakers, and curriculum designers in Hong Kong's higher institutes and vocational institutes, where PBL is widely adopted as a core pedagogical approach, to integrate ChatGPT effectively. These strategies enhance SRL and prepare software engineering students for industry demands within the VPET framework. By focusing on curriculum design, pedagogical approaches, and institutional policies, the recommendations ensure alignment with VPET's mission to develop industry-ready professionals, fostering innovation and adaptability in Hong Kong's vocational education landscape.

5.3.2.1 Curriculum Redesign for AI Integration

VPET curricula could embed ChatGPT within PBL modules to leverage its support for SRL. Candidate-14's call to "*integrate ChatGPT proactively into assignments*" is supported by logs showing its use in project frameworks (Log 02). Curricula should redefine learning outcomes to include AI literacy, ensuring students master tools like ChatGPT for tasks like iterative design reviews or debugging (Vocational Training Council, 2020b). This aligns with industry trends, where AI tools are increasingly integral to software engineering workflows (Brynjolfsson & McAfee, 2014). For example, modules could guide students to use ChatGPT for generating work breakdown structures, fostering planning and autonomy while meeting VPET's practical focus.

5.3.2.2 Pedagogical Strategies for Effective AI Use

Educators must adopt pedagogical strategies to optimise ChatGPT's benefits while mitigating risks. Candidate-01's suggestion to "*teach students how to ask better questions*" highlights the need for prompt engineering training. Logs revealed varied query effectiveness (Log 08), indicating that workshops on crafting precise prompts can enhance AI utility. Framing ChatGPT as a complementary tool, as Candidate-13 noted ("*not a replacement for critical thinking*"), is crucial. Structured PBL tasks, such as using ChatGPT for reflective reviews (Log 06), can promote SRL while preserving analytical skills. These strategies align with Hmelo-Silver et al. (2007), who advocate for scaffolding that supports but does not supplant student agency, ensuring VPET students develop robust problem-solving skills.

5.3.2.3 Fostering Industry-Relevant Competencies

ChatGPT's integration prepares students for AI-augmented workplaces, a core VPET objective. Candidate-09's observation, "*Learning it builds job competitiveness*", is reflected in logs showing support for tasks like Git configuration (Log 05), mirroring industry practices. Curricula should incorporate AI-assisted simulations, such as developing software prototypes with ChatGPT's input, to bridge academic and professional contexts. This approach fosters adaptability and technical proficiency, essential for software engineering careers (Gao & Yang, 2023). By embedding such simulations, VPET can ensure students are equipped for dynamic industry demands, enhancing employability.

5.3.2.4 Balancing AI and Independent Learning

To prevent dependency, curricula must balance AI use with independent skill development. Candidate-04's admission, "*I rely on it too much*", and logs showing repetitive task assistance (Log 03) highlight this risk. PBL tasks should require students to validate AI outputs, as Candidate-06 practiced, fostering critical engagement. Collaborative projects where ChatGPT supports planning but not execution can maintain teamwork and communication skills, vital for VPET's software engineering focus (Zimmerman, 2002). Institutional policies should enforce guidelines on AI use to uphold academic integrity, addressing concerns like Candidate-12's warning about students *"dumping everything in there".* These measures ensure students develop both AI proficiency and traditional competencies.

5.3.2.5 Addressing Resource Constraints

ChatGPT's scalability offers a practical solution to VPET's resource constraints, such as limited instructor availability (Aldabbus, 2018). Its 24/7 support (Candidate-07) reduced educator workload, enabling more focus on mentorship. Policymakers should invest in AI infrastructure and training to integrate tools like ChatGPT across VPET institutions, ensuring equitable access. This aligns with the HKSAR Education Bureau's (2020) goal of flexible, inclusive education pathways, enhancing VPET's capacity to deliver high-quality training.

5.4 Limitations and Future Research

This section critically evaluates the limitations of the current study and proposes directions for future research to address these constraints and extend the study's contributions. Acknowledging limitations ensures a transparent interpretation of the findings, while outlining future research directions provides a roadmap for advancing knowledge in the field.

5.4.1 Limitations of the Study

The current study offers new insights, but several limitations must be recognised to contextualise its findings and guide future improvements. These limitations arise from methodological choices, sample characteristics, data collection challenges, and external factors affecting the study's scope and generalisability. Table 5.1 summarises the key limitations and corresponding future research strategies, visually linking methodological constraints to actionable directions for advancing the study of AI-supported PBL and SRL.

Limitation	Description	Future Research Direction
Demographic Limitations	Study limited to a single vocational institution in Hong Kong, potentially restricting generalisability to other contexts	Conduct comparative studies across multiple institutions and cultural contexts, identifying common patterns and context-specific factors

Limitation	Description	Future Research Direction
Methodological Design Constraints	Quasi-experimental design with potential selection bias; sequential data collection with possible recall effects.	Implement randomised controlled trials where feasible; conduct longitudinal studies tracking sustained effects; employ concurrent mixed-methods data collection
Single Module Implementation	Focus on one module within a single semester, without iteration or cross-curricular integration	Investigate ChatGPT across multiple modules within a program; conduct longitudinal studies spanning entire program curricula to examine cumulative effects
Single AI Tool Focus	Exclusive focus on ChatGPT limits generalisability to other AI systems with different capabilities	Compare multiple conversational AI tools and versions to identify which features best support specific SRL components in PBL settings
Voluntary Participation Environment	Voluntary enrolment potentially creating selection bias and lacking high-stakes academic pressures	Examine AI integration in high-stakes academic environments with performance evaluation pressure; compare outcomes between voluntary and required implementations; employ methodologies like crossover trial design to mitigate potential ethical issues
Data Collection and Instrumentation	Instruments may oversimplify constructs; resource constraints limit data depth	Develop multidimensional tools and use objective measures or technology for real-time data collection.
External and Contextual Influences	Rapid AI advancement and regional access limitations (ChatGPT officially unavailable in Hong Kong) affecting implementation.	Design studies accounting for technological evolution and regional constraints; investigate implementation approaches suitable for areas with limited AI access

Limitation	Description	Future Research Direction
Scope and Variable Selection	Focus on specific variables excludes other relevant factors	Explore additional variables and interdisciplinary perspectives to broaden understanding

Table 5.1 Summary of limitations and corresponding future research strategies

Demographic Limitations: The study was run in a single vocational education institution in Hong Kong, which may not represent software engineering students in other settings or regions. Cultural, educational, and socioeconomic factors specific to this population could shape the results, limiting generalisability to broader contexts and different cultural backgrounds.

Methodological Design Constraints: The sequential explanatory mixed-methods quasi-experimental design offered complementary insights but has limits. The lack of full randomisation, constrained by the educational context, may have introduced selection bias despite attempts to balance groups by academic performance. The sequential timing also introduced a lag between quantitative and qualitative phases that could have affected participants' recall and perceptions.

Single Module Implementation: The study focused exclusively on one module within a single semester, without iteration or longitudinal tracking across multiple courses. This design may miss variations in ChatGPT's impact across subjects, project complexities, or stages of study. It also cannot reveal cumulative or cross-course effects that might appear across an entire programme.

Single AI Tool Focus: The study concentrated exclusively on ChatGPT as the conversational AI tool, which limits the generalisability of findings to other AI models. Different systems vary in capabilities, interfaces, and constraints, and may influence SRL differently in PBL environments. This narrow tool focus restricts broader conclusions about conversational AI in education.

Voluntary Participation Environment: Voluntary enrolment may have attracted students more open to technological innovation, creating selection bias. Such conditions differ from mandatory settings where performance pressure, deadlines, and evaluation stress are salient. The absence of high-stakes consequences may have shaped engagement patterns and produced more positive outcomes than might occur in standard academic contexts.

Data Collection and Instrumentation: The instruments used for data collection, although validated, may not fully capture the complexity of the phenomenon under investigation. Surveys and interview protocols can oversimplify multifaceted constructs, yielding incomplete insights. Time and resource constraints limited data depth and precluded supplementary methods such as observational data or secondary sources that could strengthen validity.

External and Contextual Influences: The study occurred during a period of rapid AI advancement, with new models and capabilities emerging frequently. Political and regulatory factors also shaped access in Hong Kong, where ChatGPT was not officially available and access often occurred through alternative platforms with reduced functionality. These conditions likely influenced engagement and perceived utility, limiting applicability to contexts with different access landscapes.

Scope and Variable Selection: The study focused on a defined set of variables, which, while necessary to maintain focus, excluded other potentially relevant factors. For example, unexamined mediators or moderators could influence the relationships observed, providing only a partial understanding of the research problem. This limitation reflects practical constraints but highlights the need for broader investigations in future research.

5.4.2 Future Research Directions

The limitations identified provide a foundation for future research to build upon the current study's findings. The following directions aim to address methodological constraints, enhance generalisability, and explore new dimensions of the research problem.

Diversifying Institutional and Cultural Contexts: Future research should examine ChatGPT's impact on SRL across multiple institutions and cultural settings. Comparative studies across vocational education institutions in Hong Kong and abroad can test robustness across educational systems, pedagogical traditions, and student populations. Such work would improve generalisability and reveal context-specific factors shaping AI effectiveness.

Strengthening Methodological Approaches: More rigorous experimental designs, with random assignment where feasible, would bolster causal inference. Longitudinal studies across semesters or academic years can illuminate sustained effects on learning behaviours and skill development. Concurrent mixed-methods designs can reduce recall bias and better integrate quantitative outcomes with qualitative experiences.

Implementing Cross-Curricular Studies: Researchers should investigate ChatGPT's impact across multiple modules within a programme, assessing how AI functions across subject matters and project types. Longitudinal designs spanning entire curricula could reveal cumulative effects and synergies from cross-course integration, informing optimal patterns across educational stages and content areas.

Exploring Diverse AI Tools and Comparative Analysis: Studies should compare multiple conversational AI systems to evaluate support for SRL in PBL contexts. Comparing ChatGPT with other large language models or different versions of the same system can identify features that most effectively support specific SRL dimensions, yielding more generalisable insights into AI's educational potential.

Examining High-Stakes Implementation: Research should explore AI use in high-stakes settings marked by performance anxiety, evaluation pressure, and meaningful academic consequences. Comparing voluntary with required implementations can clarify how stressors shape AI effectiveness and student receptivity, offering realistic guidance for large-scale curricular adoption. However, adopting the research design of this study may cause ethical concerns for placing the control group in a potentially disadvantage position with no access to ChatGPT. It is therefore suggested to employ other methodologies like crossover trial design to mitigate the issue.

Enhancing Data Collection Methods: Developing and validating instruments tailored to AI-enhanced learning can improve measurement precision. Combining self-reports with behavioural metrics such as AI interaction logs, project artefacts, and observations can triangulate findings and limit bias, providing a more comprehensive view of AI's influence on learning processes.

Investigating Contextual Variability: Studies should examine how regional AI access policies, institutional technology strategies, and rapidly evolving AI capabilities affect outcomes. Designs that account for these external factors can produce more robust, future-proof insights. Research on alternative implementations suited to regions with limited AI access would increase practical relevance.

Broadening the Research Scope: Expanding variables to include mediators and moderators can clarify how and why AI affects SRL. Factors such as prior programming experience, AI literacy, learning preferences, and technological self-efficacy may shape the AI–learning nexus. Examining ChatGPT across software engineering tasks and knowledge domains can pinpoint where support is most beneficial.

Finally, future research should focus on translating findings into actionable interventions or policies. Pilot studies or action research could test the feasibility and effectiveness of programs based on the study's results, bridging the gap between theory and practice. Collaborative efforts with practitioners or policymakers could ensure that research outcomes address real-world needs.

5.5 Reflections and Conclusion

Reflecting on the research as a whole, this section presents the reflective insights on the research journey and concluding synthesis of the project. It concludes with a final statement highlighting the study's significance for VPET pedagogy and its implications for future advancements in educational technology.

5.5.1 Reflective Insights on the Research Journey

As a programme leader and module lecturer at V-Institute, integrating ChatGPT into PBL proved challenging yet transformative, given VPET's resource constraints such as limited time, human resources, and access to experts (Aldabbus, 2018). These issues often hindered timely student support and project quality.

Throughout the study, I observed ChatGPT's versatility as a virtual group member, expert consultant, and teacher. Logs showed its effectiveness in providing real-time debugging and planning support (Log 03, Log 04), reducing instructor workload and improving student efficiency.

However, concerns were identified: some students admitted copying ChatGPT outputs without verification due to deadlines, as one interviewee stated, "When deadlines approach, I sometimes just take what ChatGPT gives me without checking if it's actually correct." This raises issues of authentic learning, especially for underperforming students who may lack the knowledge to evaluate AI content responsibly, creating a potential paradox in AI-assisted education.

Despite these risks, observing project evolution was gratifying. Student work grew more sophisticated, incorporating advanced features like Chart.js visualisations and optimised database designs (Log 06, Log 02). ChatGPT scaffolded complex tasks, enabling focus on higher-order design and aligning with VPET's industry-ready objectives (Vocational Training Council, 2020a).

Initial fears of over-reliance were alleviated by encouraging findings. MSLQ data indicated significant SRL improvements, particularly in effort regulation and help-seeking, while interviews revealed students treating ChatGPT as a supportive tool for deeper exploration. Key SRL factors like planning, monitoring, and reflection were enhanced, fostering autonomy and metacognition in line with VPET goals.

ChatGPT's integration also reshaped the teacher's role. Initially, I worried it might diminish instructors to secondary facilitators by providing instant responses. Instead, it elevated us to guides of innovation and critical thinking, emphasising holistic design, edge cases, and inquiry-based mentorship (Darling-Hammond et al., 2009). This shift promoted intellectual rigor and creativity in the classroom.

Furthermore, PBL with ChatGPT mirrored AI-augmented workplaces, where tools streamline coding and management. This alignment reinforces VPET's need to prepare students for such environments through critical AI engagement, preserving mentorship's role in building adaptability and industry skills (Barron & Darling-Hammond, 2008).

Personally, this journey deepened my view of educational technology. Starting with a focus on SRL enhancement, I gained appreciation for the interplay of tools, pedagogy, and student agency. While AI offers personalisation and efficiency, its success hinges on thoughtful ecosystem design to mitigate dependency and verification challenges.

5.5.2 Concluding Synthesis of the Project

The V-Institute study found that integrating ChatGPT into project-based learning can enhance self-regulated learning and provide a scalable response to VPET’s pedagogical needs. Quantitatively, students using ChatGPT showed significant gains in effort regulation and help-seeking ($p<0.05$), modest improvements in final scores ($M=60.3$ vs. 55.8, $p=0.041$), and lower score variability ($SD=13.3$ vs. 21.6), suggesting more consistent performance. Qualitatively, ChatGPT supported forethought, performance, and reflection through tailored guidance, debugging, and reflective reviews (Log 04, Log 06), aligning with VPET's emphasis on practical skills (HKSAR Education Bureau, 2020).

Personalised and time-efficient assistance enabled more sophisticated projects (Log 06). Constraints included difficulty with large codebases and accuracy issues that required verification, as students noted the risk of hallucination (Candidate-14). Concerns about dependency highlight the need for balanced curriculum design in VPET's software engineering education (Hmelo-Silver et al., 2007).

Problem-solving benefited through rapid technical resolutions and verification habits (Log 05). Effects on teamwork and communication were mixed. Some students reported reduced interaction, while others experienced greater inclusion and took on coding tasks they would typically avoid (Candidate-15). These patterns suggest the importance of structured AI integration to preserve collaborative competencies vital to software engineering teams (Vocational Training Council, 2020b).

The study extends SRL and PBL frameworks by positioning AI as a mediator of autonomy and metacognition, elaborating Zimmerman's model (2002). It recommends curriculum redesign that embeds AI literacy and prompt engineering to develop industry-ready skills while nurturing critical thinking and collaboration (Gao & Yang, 2023). In VPET contexts, ChatGPT can help ease resource constraints and allow educators to focus on mentorship and inquiry.

Limitations include potential bias from self-reported data and limited generalizability. Future research should involve larger samples, longitudinal designs, cross-disciplinary settings, and exploration of advanced or multimodal AI to strengthen the scalability and effectiveness of PBL.

Final Statement

This study highlights ChatGPT's transformative role in VPET, boosting self-regulated learning (SRL) in problem-based learning (PBL) environments to ready software engineering students for AI-driven industries. It cultivates autonomy, critical thinking, and practical skills, tackling VPET challenges like resource shortages, while yielding modest academic improvements and steady performance. ChatGPT's personalised guidance, efficiency, and debugging aid enable advanced, industry-aligned projects, supporting VPET's goal of professional development. However, challenges such as dependency risks, technical limitations, and variable teamwork impacts require strategic curriculum design, integrating AI literacy, prompt engineering, and balanced collaborative tasks for holistic skill development. This research illuminates innovative pedagogy, repositioning teachers as mentors of critical inquiry and strengthening VPET’s industry readiness focus. As AI reshapes workplaces, it advocates thoughtful AI integration in vocational education: a scalable approach empowering students to excel in tech-driven environments while upholding intellectual rigor and collaborative essence vital for software engineering.

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Appendix One: Participant Information Sheets

Lancaster University

Department of Educational Research
County South, Lancaster University, LA1 4YD, UK
Tel: +44 (0) 1524 592685

Investigate the Role of Conversational AI in Promoting Self-Regulated Learning in Project-based Learning for Software Engineering Students for Vocational Education

Participant Information Sheet

My name is KWOK Yu Ho and I am a PhD student studying in the Department of Educational Research at Lancaster University. I would like to invite you to take part in a research project on **Investigate the Role of Conversational AI in Promoting Self-Regulated Learning in Project-based Learning for Software Engineering Students for Vocational Education.**

Before you decide if you wish to take part, you need to understand why the research is being done and what it would involve for you. Please take time to read the following information carefully. Talk to others about the study if you wish. Ask me if there is anything that is not clear or if you would like more information. Take time to decide whether or not you wish to take part.

What is the study about?

This PhD research aims to investigate the role of ChatGPT, an advanced language model, in promoting self-regulated learning within the context of Project-Based Learning (PBL) for software engineering students at the Hong Kong Institute of Vocational Education (IVE). The study seeks to understand how ChatGPT can be integrated into PBL activities to facilitate self-regulated learning and improve students' overall learning experience. By participating in this research, you will be contributing to the exploration of innovative ways to enhance vocational education and training. Your experiences and feedback will help to evaluate the effectiveness of ChatGPT in PBL settings and provide valuable insights into the potential benefits, challenges, and implications of incorporating AI-powered tools in vocational education.

Why have I been asked to take part?

You have been asked to take part in this research because you are a software engineering student involved in a Project-Based Learning (PBL) module at the Hong Kong Institute of Vocational Education (IVE). Your experiences, opinions, and insights as a participant in PBL activities are essential for understanding how ChatGPT can be integrated to support self-regulated learning and enhance the overall learning experience. Your participation will contribute to the development of innovative strategies for improving vocational education and training, specifically in the context of software engineering.

What will happen during the study?

During the study, you will be asked to engage with ChatGPT as part of your regular Project-Based Learning (PBL) activities. You will be chosen, or chosen not to use ChatGPT to support your self-regulated learning, ask questions, and collaborate with your peers on the project. We will collect and analyse data from questionnaires, the usage log of ChatGPT for this module, assessment results to assess the impact on your learning experience. In addition, you may be asked to participate in semi-structured interviews to share your experiences using ChatGPT in the PBL context.

Your participation in this study will require minimal additional time commitment beyond your regular PBL activities. The interviews and focus groups, if you are selected to participate in them, will last approximately 30-60 minutes each. These sessions will be scheduled at your convenience to minimize any disruption to your academic commitments.

How do I give my consent to take part?

Firstly, you are asked to read this sheet fully and make sure you understand all parts of the study. If you have any questions, you can email me, (Kwok Yu Ho (Will), **kwokyh1@lancaster.ac.uk**).
If you have no remaining questions, and are happy to take part, please fill in the attached consent form and send it back as a scanned copy to me, (Kwok Yu Ho (Will), **kwokyh1@lancaster.ac.uk**). I will then be in touch to confirm further details.

What if I do not want to take part, or if I change my mind?

Participation in the study is entirely voluntary. If you do not wish to take part then that is not a problem. You do not need to take any action.

You might wish to change your mind after initially agreeing to take part, and to withdraw from the study. That is fine; please let me know as soon as you reach this decision. If you wish to stop part way through the interview, that is also no problem, just let me know and the interview will stop, and your data will not be used in the study.

You might decide after the interview that you are no longer happy for your information to be used. If you decide to withdraw after the study, and contact me within **one week** of the interview, your data will be destroyed and not used. After this point, the research analysis of the data will have commenced, and your data will remain in the study.

Refusal to take part, changing your mind or withdrawing from the study will not involve a penalty of any kind and will have no bearing on our relationship or any institution associated with the study. Also, it will not affect your studies, learning or marks.

How will my information be stored and who will have access to it?

All information collected from you (interview responses and documents) will be stored in a dedicated, password-protected computer folder and will only be accessible to myself. Data (whether written or audio) will not be stored with any names or other identifying information, and any transcripts will not be accessible to anyone other than myself. If, for any reason, you would like a copy of the information you provided after the study is completed, then please email me.

All information generated by the project will be stored in the secure computer folder, in line with the requirements of the Data Protection Act and Lancaster University Research Ethics Committee requirements.

Any publications or presentations arising from this project will not identify you by name, with pseudonyms being used instead. When presenting transcripts and other research data in publications or presentations, I shall also strive to limit the excerpts so that you are not easily identifiable; there is however, always a very small risk that your participation in this study could be identifiable.

What are the potential risks or benefits involved for me in the study?

There are no particular risks identified for participants who participate in this study. No confidential or sensitive information will be collected. All information that could identify you will be removed before the data are analysed, though I need to remind you once again that I cannot fully guarantee your anonymity as discussed in the previous section.

The benefits of participating are indirect, since it is not possible for me to offer any financial incentive or any expenses for participants for this project.

Who has reviewed this project?

Ethical approval for this study has been obtained from the Department of Educational Research, Lancaster University.

Contact details for the researcher

Name : Kwok Yu Ho
Tel.: 2256 7306
Email: kwokyh1@lancaster.ac.uk / kwokyuho@vtc.edu.hk

Who else can I contact

If you are concerned an aspect of the study or if you have a complaint, you can contact Dr Jan McArthur, the Head of Department, or my tutor Professor Don Passey:

Dr Jan McArthur Department of Educational Research, County South, Lancaster University, Lancaster, LA1 4YL, United Kingdom Email:j.mcarthur@lancaster.ac.uk	Professor Don Passey Department of Educational Research, County South, Lancaster University, Lancaster, LA1 4YL, United Kingdom Email:d.passey@lancaster.ac.uk

Appendix Two: Participant Consent Form

Investigate the Role of Conversational AI in Promoting Self-Regulated Learning in Project-based Learning for Software Engineering Students for Vocational Education

Consent Form

Researcher Name: KWOK Yu Ho
Email Address: (**kwokyh1@lancaster.ac.uk**)

Please read and then tick each box	Tick Box
1. I confirm that I have read and understand the participant information sheet for the above study. I have had the opportunity to consider the information, ask questions and have had these answered satisfactorily.	☐
2. I understand that my participation is voluntary and that I am free to withdraw at any time during my participation in this study and within one week after I took part in the study, without giving any reason. If I withdraw within 1 week of taking part in the study, my data will be removed.	☐
3. I understand that any information given by me may be used in future reports, academic articles, publications or presentations by the researcher/s, but my personal information will not be included, and I will not be identifiable.	☐
4. I understand that my name/any information that can identify me will not appear in any reports, articles or presentation without my consent.	☐
5. I understand that the data from any interviews that are audio-recorded and/or transcribed, will be protected on encrypted devices and kept secure.	☐
6. I understand that I may be asked to provide documents that influence or illustrate my practice, so long as they are written by me and do not identify other people, and that documents I provide will be kept securely.	☐
7. I understand that data will be kept according to University guidelines for a minimum of 10 years after the end of the study.	

Name of Participant………………………………………..Date…………………………………
Signature……………………………………………………

I confirm that the participant was given an opportunity to ask questions about the study, and all the questions asked by the participant have been answered correctly and to the best of my ability. I confirm that the individual has not been coerced into giving consent, and the consent has been given freely and voluntarily.

Signature of Researcher…………………………………Date…………………………………

One copy of this form will be given to the participant and the original kept in the researcher's files at Lancaster University.

Appendix Three: Institute Consent Email

Investigate the Role of Conversational AI in Promoting Self-Regulated Learning in Project-based Learning for Software Engineering Students for Vocational Education

Consent Email for Data Collection at the Department of IT, Hong Kong Institute of Vocational Education (Sha Tin)

Dear [Name of HoD],

I am writing to request your consent to collect student and instructor data for my PhD research at the Department of Educational Research, Lancaster University. As the Head of Department, I believe your support is crucial for the success of my research.

The research project is **Investigate the Role of Conversational AI in Promoting Self-Regulated Learning in Project-based Learning for Software Engineering Students for Vocational Education.** This PhD research aims to investigate the role of ChatGPT or equivalent LLM model, an advanced language model, in promoting self-regulated learning within the context of Project-Based Learning (PBL) for software engineering students at the Hong Kong Institute of Vocational Education (IVE). The study seeks to understand how ChatGPT can be integrated into PBL activities to facilitate self-regulated learning and improve students' overall learning experience. In this study, your students and lecturers will be invited to take part in pre-test and post-test assessments, and semi-structured interviews. The study will also collect students' marks for data analysis.

I would like to assure you that all data collected for this research will be kept anonymous and confidential. The data will be stored in password-protected storage, and access will only be granted to authorized personnel involved in the research. Additionally, students and instructors will have the option to opt-out of the research without any consequences. My research aims to explore the effectiveness of certain teaching methods in improving student learning outcomes. The data collected will be used solely for this purpose and will not be shared with any third parties.

I understand that the privacy and confidentiality of student and instructor data are of utmost importance, and I assure you that I will take all necessary measures to ensure that the data are kept secure and confidential.

I would be grateful for your consent to collect the data necessary for my research. Thank you for your time and consideration. I look forward to hearing from you soon.

Best regards,
Yu Ho Kwok
Senior Lecturer, Dept of IT, IVE(ST), and
Postgraduate Researcher, Lancaster University

Appendix Four: Motivated Strategies for Learning Questionnaire

Investigate the Role of Conversational AI in Promoting Self-Regulated Learning in Project-based Learning for Software Engineering Students for Vocational Education

Motivated Strategies for Learning Questionnaire

1.	In a class like this, I prefer course material that really challenges me so I can learn new things.	1	2	3	4	5	6	7
2.	If I study in appropriate ways, then I will be able to learn the material in this course.	1	2	3	4	5	6	7
3.	When I take a test I think about how poorly I am doing compared with other students.	1	2	3	4	5	6	7
4.	I think I will be able to use what I learn in this course in other courses.	1	2	3	4	5	6	7
5.	I believe I will receive an excellent grade in this class.	1	2	3	4	5	6	7
6.	I'm certain I can understand the most difficult material presented in the readings for this course.	1	2	3	4	5	6	7
7.	Getting a good grade in this class is the most satisfying thing for me right now.	1	2	3	4	5	6	7
8.	When I take a test I think about items on other parts of the test I can't answer.	1	2	3	4	5	6	7
9.	It is my own fault if I don't learn the material in this course.	1	2	3	4	5	6	7

10.	It is important for me to learn the course material in this class.	1	2	3	4	5	6	7
11.	The most important thing for me right now is improving my overall grade point average, so my main concern in this class is getting a good grade.	1	2	3	4	5	6	7
12.	I'm confident I can learn the basic concepts taught in this course.	1	2	3	4	5	6	7
13.	If I can, I want to get better grades in this class than most of the other students.	1	2	3	4	5	6	7
14.	When I take tests I think of the consequences of failing.	1	2	3	4	5	6	7
15.	I'm confident I can understand the most complex material presented by the instructor in this course.	1	2	3	4	5	6	7
16.	In a class like this, I prefer course material that arouses my curiosity, even if it is difficult to learn.	1	2	3	4	5	6	7
17.	I am very interested in the content area of this course.	1	2	3	4	5	6	7
18.	If I try hard enough, then I will understand the course material.	1	2	3	4	5	6	7
19.	I have an uneasy, upset feeling when I take an exam.	1	2	3	4	5	6	7
20.	I'm confident I can do an excellent job on the assignments and tests in this course.	1	2	3	4	5	6	7
21.	I expect to do well in this class.	1	2	3	4	5	6	7

22.	The most satisfying thing for me in this course is trying to understand the content as thoroughly as possible.	1	2	3	4	5	6	7
23.	I think the course material in this class is useful for me to learn.	1	2	3	4	5	6	7
24.	When I have the opportunity in this class, I choose course assignments that I can learn from even if they don't guarantee a good grade.	1	2	3	4	5	6	7
25.	If I don't understand the course material, it is because I didn't try hard enough.	1	2	3	4	5	6	7
26.	I like the subject matter of this course.	1	2	3	4	5	6	7
27.	Understanding the subject matter of this course is very important to me.	1	2	3	4	5	6	7
28.	I feel my heart beating fast when I take an exam.	1	2	3	4	5	6	7
29.	I'm certain I can master the skills being taught in this class.	1	2	3	4	5	6	7
30.	I want to do well in this class because it is important to show my ability to my family, friends, employer, or others.	1	2	3	4	5	6	7
31.	Considering the difficulty of this course, the teacher, and my skills, I think I will do well in this class.	1	2	3	4	5	6	7
32.	When I study the readings for this course, I outline the material to help me organize my thoughts.	1	2	3	4	5	6	7

33. During class time I often miss important points because I'm thinking of other things.	1	2	3	4	5	6	7
34. When studying for this course, I often try to explain the material to a classmate or friend.	1	2	3	4	5	6	7
35. I usually study in a place where I can concentrate on my course work.	1	2	3	4	5	6	7
36. When reading for this course, I make up questions to help focus my reading.	1	2	3	4	5	6	7
37. I often feel so lazy or bored when I study for this class that I quit before I finish what I planned to do.	1	2	3	4	5	6	7
38. I often find myself questioning things I hear or read in this course to decide if I find them convincing.	1	2	3	4	5	6	7
39. When I study for this class, I practice saying the material to myself over and over.	1	2	3	4	5	6	7
40. Even if I have trouble learning the material in this class, I try to do the work on my own, without help from anyone.	1	2	3	4	5	6	7
41. When I become confused about something I'm reading for this class, I go back and try to figure it out.	1	2	3	4	5	6	7
42. When I study for this course, I go through the readings and my class notes and try to find the most important ideas.	1	2	3	4	5	6	7
43. I make good use of my study time for this course.	1	2	3	4	5	6	7

44. If course readings are difficult to understand, I change the way I read the material.	1	2	3	4	5	6	7
45. I try to work with other students from this class to complete the course assignments.	1	2	3	4	5	6	7
46. When studying for this course, I read my class notes and the course readings over and over again.	1	2	3	4	5	6	7
47. When a theory, interpretation, or conclusion is presented in class or in the readings, I try to decide if there is good supporting evidence.	1	2	3	4	5	6	7
48. I work hard to do well in this class even if I don't like what we are doing.	1	2	3	4	5	6	7
49. I make simple charts, diagrams, or tables to help me organize course material.	1	2	3	4	5	6	7
50. When studying for this course, I often set aside time to discuss course material with a group of students from the class.	1	2	3	4	5	6	7
51. I treat the course material as a starting point and try to develop my own ideas about it.	1	2	3	4	5	6	7
52. I find it hard to stick to a study schedule.	1	2	3	4	5	6	7
53. When I study for this class, I pull together information from different sources, such as lectures, readings, and discussions.	1	2	3	4	5	6	7
54. Before I study new course material thoroughly, I often skim it to see how it is organized.	1	2	3	4	5	6	7

55.	I ask myself questions to make sure I understand the material I have been studying in this class.	1	2	3	4	5	6	7
56.	I try to change the way I study in order to fit the course requirements and the instructor's teaching style.	1	2	3	4	5	6	7
57.	I often find that I have been reading for this class but don't know what it was all about.	1	2	3	4	5	6	7
58.	I ask the instructor to clarify concepts I don't understand well.	1	2	3	4	5	6	7
59.	I memorize key words to remind me of important concepts in this class.	1	2	3	4	5	6	7
60.	When course work is difficult, I either give up or only study the easy parts.	1	2	3	4	5	6	7
61.	I try to think through a topic and decide what I am supposed to learn from it rather than just reading it over when studying for this course.	1	2	3	4	5	6	7
62.	I try to relate ideas in this subject to those in other courses whenever possible.	1	2	3	4	5	6	7
63.	When I study for this course, I go over my class notes and make an outline of important concepts.	1	2	3	4	5	6	7
64.	When reading for this class, I try to relate the material to what I already know.	1	2	3	4	5	6	7
65.	I have a regular place set aside for studying.	1	2	3	4	5	6	7

66.	I try to play around with ideas of my own related to what I am learning in this course.	1	2	3	4	5	6	7
67.	When I study for this course, I write brief summaries of the main ideas from the readings and my class notes.	1	2	3	4	5	6	7
68.	When I can't understand the material in this course, I ask another student in this class for help.	1	2	3	4	5	6	7
69.	I try to understand the material in this class by making connections between the readings and the concepts from the lectures.	1	2	3	4	5	6	7
70.	I make sure that I keep up with the weekly readings and assignments for this course.	1	2	3	4	5	6	7
71.	Whenever I read or hear an assertion or conclusion in this class, I think about possible alternatives.	1	2	3	4	5	6	7
72.	I make lists of important items for this course and memorize the lists.	1	2	3	4	5	6	7
73.	I attend this class regularly.	1	2	3	4	5	6	7
74.	Even when course materials are dull and uninteresting, I manage to keep working until I finish.	1	2	3	4	5	6	7
75.	I try to identify students in this class whom I can ask for help if necessary.	1	2	3	4	5	6	7
76.	When studying for this course I try to determine which concepts I don't understand well.	1	2	3	4	5	6	7

77.	I often find that I don't spend very much time on this course because of other activities.	1	2	3	4	5	6	7
78.	When I study for this class, I set goals for myself in order to direct my activities in each study period.	1	2	3	4	5	6	7
79.	If I get confused taking notes in class, I make sure I sort it out afterwards.	1	2	3	4	5	6	7
80.	I rarely find time to review my notes or readings before an exam.	1	2	3	4	5	6	7
81.	I try to apply ideas from course readings in other class activities such as lecture and discussion.	1	2	3	4	5	6	7

End of the Questionnaire

Appendix Five: Semi-structured Interview Protocol

Investigate the Role of Conversational AI in Promoting Self-Regulated Learning in Project-based Learning for Software Engineering Students for Vocational Education

Semi-structured interview protocol

The following are the core questions that will be asked during the interview. Because this is a *semi-structured* interview, the researcher may ask additional questions to encourage you to expand on your responses. Those follow-up questions cannot be prepared in advance and so do not appear on this list.

Core questions

1. Can you briefly describe your experience using ChatGPT in the context of PBL?
2. How do you feel ChatGPT has influenced your learning process during PBL activities?
3. In which aspects of PBL did you find ChatGPT most helpful? Can you provide specific examples?
4. Did you encounter any challenges or limitations while using ChatGPT in your PBL activities? If so, please elaborate.
5. How do you think ChatGPT has impacted your ability to engage in self-regulated learning? Please provide examples.
6. Did you notice any changes in your collaboration with peers while using ChatGPT? If so, can you describe those changes?
7. How has ChatGPT influenced your motivation and engagement in PBL activities?
8. In your opinion, what are the most significant advantages of incorporating ChatGPT into PBL settings?
9. Are there any areas where you think ChatGPT could be improved to better support PBL and self-regulated learning?
10. Would you recommend the integration of ChatGPT into PBL activities for other students? Why or why not?

Appendix Six: Example of a Coded Interview Transcript

One-on-One Interview Log - Facilitator and Candidate 16

Facilitator

Thank you for joining me today, Candidate 16. This is a relaxed conversation, and I'm not looking for perfect responses—your honest experiences are what make this research valuable. Let me outline the setup: our discussion will be recorded, transcribed into Chinese, and then translated into English for a UK university study. Your identity will remain fully anonymous, with no personal details included. We're recording both audio and video, but both will be deleted after transcription, leaving only the text for analysis.

I'll ask questions one at a time, and you can respond based on your perspective. Feel free to share openly, focusing on what resonates with you. We're exploring how you used ChatGPT in project-based learning (PBL), specifically for the JSP project in the 4511 course, and its impact on self-regulated learning. Let's start with the first question: What was your overall experience using ChatGPT for project-based learning in the JSP project? How did it shape your work or learning process?

Candidate 16

My experience was pretty positive. When I got stuck on something, I'd normally Google problems, but ChatGPT handled those too, just faster. It gave precise answers that fit my situation, which made the project process smoother and helped me keep moving forward without wasting time.

Facilitator

That sounds like a helpful tool. For the second question: You've worked on projects before and after ChatGPT became prevalent. How has its introduction affected your learning process in PBL? Where have you noticed the biggest changes compared to traditional methods like Google or asking teachers?

Candidate 16

It didn't change things drastically—it was just slower with Google, forums, or YouTube. ChatGPT's precise answers saved time. Google struggles with niche questions, but ChatGPT breaks down what you ask and gets it right. For example, in the JSP project, I could ask a specific question about a function and get a tailored answer, which was much faster than sifting through search results.

Facilitator

So, it's more personalized and time-efficient. For the third question: In PBL, the process involves finding a direction, consulting others, completing the project, and reflecting on the outcome. Where was ChatGPT most useful for you in the JSP project? Can you provide a specific example?

Candidate 16

Beyond what's been said, it was most useful for spotting errors. Instead of debugging forever, I'd toss the code to ChatGPT to check first. For example, in the JSP project, I had a bug that was slowing me down, and ChatGPT quickly pointed out the issue in my code, saving me from hours of trial and error. That was really handy.

Facilitator

That's a practical use case. You mentioned it's not quite an expert—how does it compare to traditional resources like Google for debugging?

Candidate 16

It's faster than Googling, but I don't fully trust it. I know how it works—an LLM trained on tons of data, not all correct. Google lets you cross-check multiple sites, but ChatGPT's either right or wrong, no in-between. Still, it's great for niche questions because it tailors advice to your specific scenario, unlike Google's broader results.

Facilitator

So, it's like a 24/7 resource for targeted questions. For the fourth question: What challenges or limitations did you face while using ChatGPT for the JSP project? Were there any specific issues that impacted your work?

Candidate 16

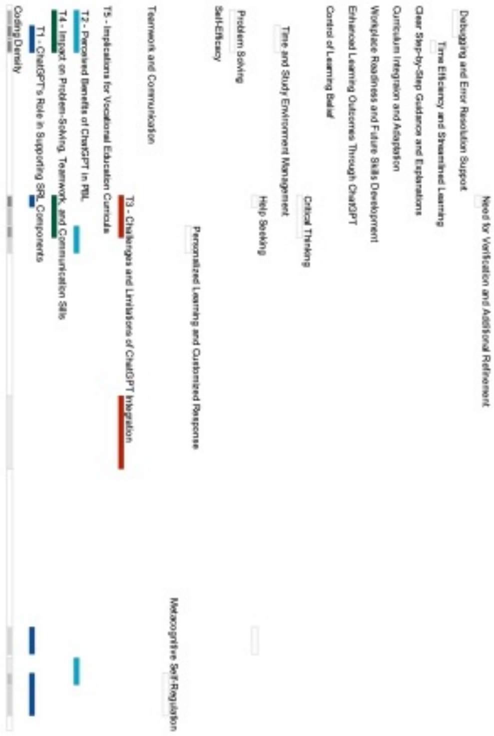
Sometimes when asking about code, it's super inconsistent. Its format might match standards one time, but other times it's weirdly complex or offbeat. You have to ask indirectly a few times to get a response—sometimes it flat-out won't answer. For example, in the JSP project, I asked for a function, and it gave me a convoluted solution that didn't fit. I had to rephrase and ask multiple times to get something usable.

Facilitator

For the fifth question: Let's explore self-regulated learning (SRL)—your ability to grow independently through motivation, like setting goals, deciding what to learn, or planning your project. Has ChatGPT helped you proactively identify what you need to learn or structure your learning for the JSP project? Can you share an example?

Candidate 16

I see it as a Google Plus—an extension. Compared to just Googling before, it's more detailed and precise, answering what I don't know better. I like treating it as a tool, like flashcards for studying. Before, I'd write exam questions myself; now, I ask ChatGPT to make similar questions and quiz me back. For example, in the JSP project, I used it to generate practice questions on server-side logic, which helped me identify gaps in my understanding and focus my learning on those areas. It made studying more interactive and targeted.



Facilitator

That's a creative use for self-assessment. For the sixth question: Has ChatGPT changed how you collaborated with teammates in the JSP project compared to before it was available? How has it affected group dynamics or task division?

Candidate 16

It speeds everyone up, especially covering a big issue for us: weak English. With AI, we're all superhuman. English fixes used to take time—now we can focus on other tasks. Even Chinglish gets cleaned up; grammar's perfect. We handle less together, but the catch is trusting AI and teammates to pick options, which impacts things a bit. For example, in the JSP project, I relied on ChatGPT to polish my report sections, so I didn't need as much team input, but sometimes teammates trusted its outputs too much, leading to minor conflicts when they didn't align.

Facilitator

Does it feel like ChatGPT acts as a teammate, covering your weaknesses, like English?

Candidate 16

Not really—just a tool, like a calculator. It perfects things but can't stand alone. You can't dump everything on it and be done—it needs oversight and basic know-how to work. For instance, it helped with English, but I still had to ensure the content made sense for the JSP project's goals.

Facilitator

For the seventh question: Did using ChatGPT make you more motivated or engaged to complete the JSP project?

Candidate 16

Yeah, it boosted my motivation. Knowing I could quickly resolve issues, like code errors or unclear guidelines, kept me engaged. For example, when I was stuck on a JSP bug, ChatGPT's fast suggestion gave me confidence to keep going, making the project feel less daunting.

Facilitator

For the eighth question: What's the biggest advantage ChatGPT brings to your learning in PBL compared to traditional methods, like asking teachers or using Google?

Candidate 16

Its ability to break down unclear guidelines is huge. If a project guideline is vague, I can feed it to ChatGPT and ask for a three-part breakdown, which clarifies what to do. For example, in the JSP project, it took a confusing requirement document and outlined the key steps, saving me from guessing.

Unlike teachers, who aren't always available, or Google, which gives broad results, ChatGPT tailors answers to my specific needs, making learning faster and more practical.

Facilitator

That targeted clarity is a key strength. For the ninth question: How could ChatGPT be improved to better support PBL or self-regulated learning? Are there specific enhancements you'd suggest to OpenAI or me as your teacher?

Candidate 16

I don't have issues with ChatGPT itself—sometimes it stalls or gives odd responses, and I'm fine with that. My main gripe is how we interact with it. The process is clunky—I spend time copying, pasting, and pulling answers out. It's annoying. The latest launch mentioned it can see your screen and chat, which is better, but it's not Iron Man-level yet, like Jarvis. If it could be zero-contact—just talk to it naturally—that'd be way easier. For example, in the JSP project, verbally explaining a bug and getting an instant response would've saved time compared to typing everything out.

Facilitator

That's a practical call for smoother interaction. For the tenth question: Would you recommend that schools encourage students to use ChatGPT for PBL projects, like the JSP course? Why or why not?

Candidate 16

I'd recommend it, but for a different reason than others. AI's the future—schools should teach students to use it sooner rather than later. For example, in the JSP project, it helped me debug and clarify requirements, skills I'll need in jobs where AI is common. But the curriculum should shift too—focus on practical AI use instead of outdated methods. It's like using a ballpoint pen instead of a quill. Students need to understand how to wield it effectively to stay competitive.

Facilitator

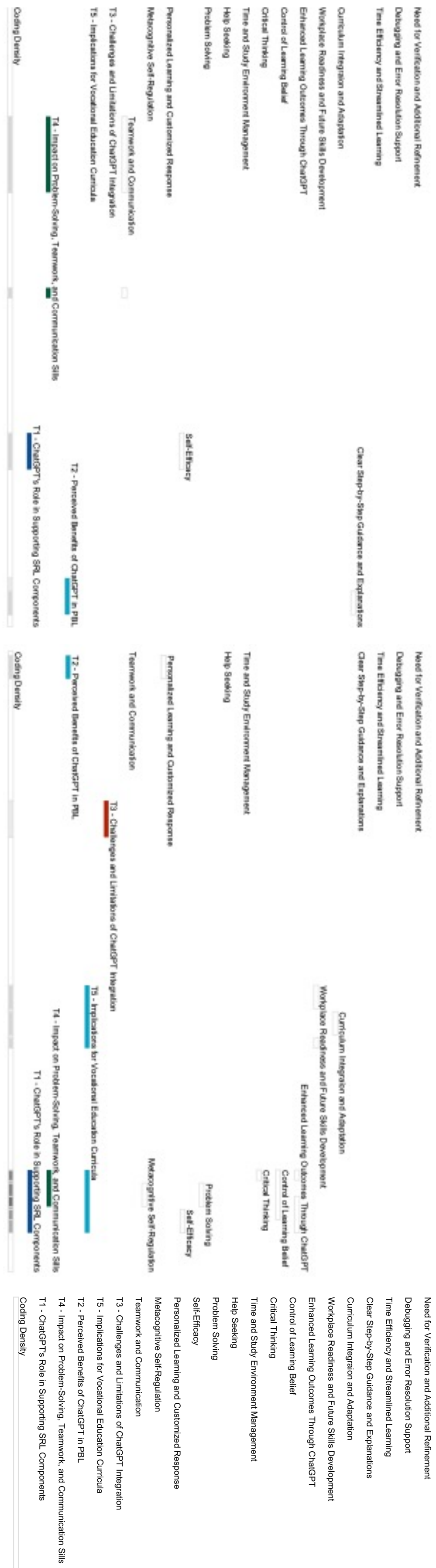
Final follow-up: Reflecting on the JSP project, did using ChatGPT help you learn the course's intended content, or did it feel like you relied on it too much, just completing the project without fully grasping the material?

Candidate 16

I think I learned, but you need a base to use it well—it's not just given to you. That base is what you've learned in the course, and ChatGPT enhances it. For example, in the JSP project, it helped me understand server-side connections better by explaining concepts I'd only partially grasped in class. I didn't just rely on it to finish—I used it to deepen my knowledge, so I learned the material, not just completed the project.

Facilitator

That's a thoughtful reflection on enhanced learning. Thank you, Candidate 16, for sharing such detailed and insightful responses. This has been incredibly valuable for the research.



Appendix Seven: Summary of Qualitative Findings by Participant

Participant ID	Key Themes Identifies	Supporting Evidence	Link to SRL Phases/PBL Elements
Candidate 01	ChatGPT's Role in Supporting SRL Components; Perceived Benefits of ChatGPT in PBL; Impact on Problem-Solving, Teamwork, and Communication Skills; Implications for Vocational Education Curricula	- "Sometimes, it even pointed out gaps in my understanding, like concepts I hadn't grasped, which made me more thorough." (Metacognitive Self-Regulation) - *"now I ask ChatGPT, get a quick answer, and have a clear path forward, so I don't get stuck. Finishing tasks fast gives a sense of accomplishment, which boosts my confidence and makes me more eager to contribute"* (Self-Efficacy) - *"The biggest thing is it saves time"* (Time and Study Environment) " - *"When our group hit a creative block, we'd ask ChatGPT for ideas. It sparked creativity and helped us analyze problems from new angles"* (Enhanced Creativity and Idea Generation) - *"We'd start with an idea, but sometimes we'd get stuck halfway and run out of inspiration"* (Problem-Solving) - *"with ChatGPT, I have to think through my questions clearly first, which makes me more organised"* (Critical Thinking) - *"It's efficient. It answers come fast, saving time for deeper learning"* (Time Efficiency and Streamlined Learning) - *"teaching students how to ask better questions and follow up would make it more valuable for learning"* (Pedagogical Strategies for Effective ChatGPT) - *"If you're not just asking ChatGPT for exam answers to memorize, but actually understanding its explanations, you're learning"* (Enhanced Learning Outcomes Through ChatGPT) - *"should encourage critical thinking more" and "could guide us to think by asking counter-questions or offering different angles".* (Balancing AI Assistance with Independent Thinking)	SRL: Forethought (planning, self-efficacy), Performance (monitoring, time management), Self-Reflection (evaluation, verification); PBL: Project Launch (idea generation), Build Knowledge (problem-solving), Develop & Critique (critical thinking), Present Products (learning outcomes)
Candidate 02	ChatGPT's Role in Supporting SRL Components; Challenges and Limitations of ChatGPT Integration; Impact	- *"It broke the project down into clear steps, so I could see the workflow and follow it"* (Metacognitive Self-Regulation) - *"with ChatGPT, I can ask anything without hesitation"* (Help-Seeking) - *"If you want detailed answers, you have to ask step by step—it can't handle huge or complex info all at*	SRL: Forethought (planning), Performance (monitoring, help-seeking), Self-Reflection (evaluation); PBL:

Participant ID	Key Themes Identifies	Supporting Evidence	Link to SRL Phases/PBL Elements
	on Problem-Solving, Teamwork, and Communication Skills	*once"* (Technical Limitation in Complex Task Management) - *"I had to figure out where it went wrong, tweak the code, and keep refining it. That process of questioning and adjusting really sharpened my critical thinking"* (Critical Thinking)	Build Knowledge (structured guidance), Develop & Critique (refinement, critical analysis)
Candidate 03	Perceived Benefits of ChatGPT in PBL; Implications for Vocational Education Curricula	- *"When I was stuck with Java programming tasks, ChatGPT guided me through each step until I could solve it myself"* (Personalised Guidance and Step-by-step Explanations) - *"I think it's a great idea. ChatGPT helps me learn the subject's content faster"* (Curriculum Integration and Adaptation)	SRL: Performance (guidance); PBL: Build Knowledge (step-by-step), Develop & Critique (content mastery)
Candidate 04	Perceived Benefits of ChatGPT in PBL; Challenges and Limitations of ChatGPT Integration; Impact on Problem-Solving, Teamwork, and Communication Skills; Implications for Vocational Education Curricula	- *"If I still don't understand, I can ask for a simpler explanation, and it adjusts to my level"* (Personalised Guidance and Step-by-step Explanations) - *"For instance, one time a function I coded wasn't working, and after I described the error, ChatGPT gave me a fix that made it run properly"* (Debugging and Error Resolution Support) - *"Sometimes you give it requirements, and the code it generates doesn't work as expected. You ask again, but it still might not get it right, so you end up scrapping that part and doing it yourself"* (Verification Requirements and Accuracy Concerns) - *"I rely on it too much, so I wait until the last minute to ask, which makes me feel lazy"* and *"It gives me code so easily that I feel like there's no rush"* (Risk of Dependency and Reduced Learning Effort) - *"Fixing my broken code was the biggest help. I'd send it back, explain the mistake in detail, and it would come back with better or correct code"* (Problem-Solving) - *"In class, with one teacher and lots of students, you don't always feel comfortable asking questions"* (Personalised Learning Enhancement)	SRL: Performance (adaptive learning, debugging), Self-Reflection (accuracy verification); PBL: Build Knowledge (personalised support), Develop & Critique (error resolution, refinement)
Candidate 05	ChatGPT's Role in Supporting SRL Components; Perceived Benefits of ChatGPT in PBL; Challenges and Limitations of ChatGPT Integration; Impact on Problem-	- *"It's made me more proactive"* (Control of Learning Belief) - *"I check the logic or Google it. I usually suspect errors after testing"* (Metacognitive Self-Regulation) - *"It helps with understanding abstract concepts I wouldn't dare ask others about"* (Help-Seeking) - *"When stuck, I didn't have to wait until the next class to continue—ChatGPT helped me overcome obstacles immediately"* (Always-Available Learning Support) - *"It doesn't always generate exactly what you need, so*	SRL: Forethought (proactive mindset), Performance (monitoring, help-seeking), Self-Reflection (verification); PBL: Build Knowledge (abstract concepts, immediate support),

Participant ID	Key Themes Identifies	Supporting Evidence	Link to SRL Phases/PBL Elements
	Solving, Teamwork, and Communication Skills	*you have to keep checking and tweaking"* (Verification Requirements and Accuracy Concerns) - *"If ChatGPT's answer matches those, I trust it; if not, I check Google or YouTube tutorials. I learned to double-check"* (Critical Thinking) - *"It's a tool that supports learning, as long as you use it thoughtfully"* (Pedagogical Strategies for Effective ChatGPT"	Develop & Critique (evaluation)
Candidate 06	Perceived Benefits of ChatGPT in PBL; Challenges and Limitations of ChatGPT Integration; Impact on Problem-Solving, Teamwork, and Communication Skills	- *"I usually take its answers and cross-check them. For coding, I check reliable sites or documents to confirm it works or if there's a better way"* (Metacognitive Self-Regulation) - *"It presents complex topics in an easier, more digestible way. If I don't understand course materials, ChatGPT explains them simply"* (Enhanced Comprehension and Information Management) - *"The time saved let me add extra features and polish my project beyond the basic requirements"* (Time Efficiency and Streamlined Learning) - *"Sometimes it forgets earlier parts of the conversation"* and *"I have to repeat code or questions because of memory lapses"* (Technical Limitation in Complex Task Management) - *"gives fake info, which can mess up your project if you don't catch it"* and *"with specialised topics, its data might not be accurate"* (Verification Requirements and Accuracy Concerns) - *"Before, I'd hit a problem, Google it, and spend days without a fix, feeling stuck and ready to give up. With ChatGPT, I ask directly, and it guides me step-by-step to the answer"* (Problem-Solving) - *"I usually take its answers and cross-check them. For data, I Google to see if similar info exists or ask it for academic sources to verify"* (Critical Thinking) - *"With ChatGPT, we can ask it for suggestions, like two tech options to choose from, and then discuss and decide. It's like a helper guiding our analysis, saving time and making choices clearer"* (Teamwork and Communication) - *"If you just copy-paste code without analyzing, it can hurt your learning. But if you're curious and dig into what it says, it's better—you learn more"* (Pedagogical Strategies for EffecitveGPT)	SRL: Performance (guidance, time saving), Self-Reflection (verification, reflection); PBL: Build Knowledge (simplification, scaffolding), Develop & Critique (analysis, decision-making)
Candidate 07	ChatGPT's Role in Supporting SRL	- *"It makes me more eager to learn on my own"* (Control of Learning Belief)	SRL: Forethought (eager learning,

Participant ID	Key Themes Identifies	Supporting Evidence	Link to SRL Phases/PBL Elements
	Components; Perceived Benefits of ChatGPT in PBL; Challenges and Limitations of ChatGPT Integration; Impact on Problem-Solving, Teamwork, and Communication Skills	- *"I used ChatGPT to create my own notes, like an outline to guide my learning"* (Metacognitive Self-Regulation) - *"I can ask simple or even silly questions I'd avoid asking a teacher, and it answers without judgment"* (Help-Seeking) - *"Having 24/7 access to help was invaluable—I could work late at night and still get answers"* (Always-Available Learning Support) - *"It sometimes forgets what I said earlier in the chat, so I have to repeat things, which gets frustrating"* (Technical Limitation in Complex Task Management) - *"The biggest issue is needing to verify its answers. It can give inaccurate info, so I have to cross-check with Google or another source to ensure it's correct"* (Verification Requirements and Accuracy Concerns) - *"I tweaked its code to match my style, like adjusting a function's approach. That deepened my understanding of the material, not just helped me finish the project"* (Critical Thinking) - *"When we disagree, we ask ChatGPT for pros and cons, which is less confrontational than arguing. It helps us pick a direction more clearly"* (Teamwork and Communication) - *"It also teaches us more—class material plus extra insights"* (Enhanced Learning Outcomes Through ChatGPT)	planning), Performance (help-seeking, access), Self-Reflection (verification, tweaking); PBL: Build Knowledge (insights), Develop & Critique (pro/con analysis, refinement)
Candidate 08	ChatGPT's Role in Supporting SRL Components; Perceived Benefits of ChatGPT in PBL; Impact on Problem-Solving, Teamwork, and Communication Skills; Implications for Vocational Education Curricula	- *"I can ask without feeling awkward, like worrying a teacher might think, 'You don't know this?' It removes those mental barriers, so I ask more freely"* (Help-Seeking) - *"handled coding questions quickly, reducing stress and letting me focus on the bigger picture"* (Time and Study Environment) - *"ChatGPT explains complicated topics in plain language that's easier to understand than technical documentation"* (Enhanced Comprehension and Information Management) - *"It saved me hours of searching through documentation and forums for solutions"* (Time Efficiency and Streamlined Learning) - *"It reduced communication with classmates" "that cuts down on team interaction, and I don't always know what teammates are thinking"* (Teamwork and Communication)	SRL: Performance (accessibility, time savings); PBL: Build Knowledge (explanations), Develop & Critique (communication)

Participant ID	Key Themes Identifies	Supporting Evidence	Link to SRL Phases/PBL Elements
		- *"ChatGPT's perfect—no pressure, and it teaches even if you don't know the technical stuff"* (Personalised Learning Enhancement) - *"teach students how to communicate with ChatGPT"* (Pedagogical Strategies for Effective ChatGPT) - *"cuts down on team interaction, and I don't always know what teammates are thinking"* (Balancing AI Assistance with Independent Thinking)	
Candidate 09	ChatGPT's Role in Supporting SRL Components; Perceived Benefits of ChatGPT in PBL; Impact on Problem-Solving, Teamwork, and Communication Skills; Implications for Vocational Education Curricula	- *"I saw it as a tool, not something to fully rely on—I'd still think for myself and not trust its answers 100%"* (Control of Learning Belief) - *"ChatGPT's right there on my phone or computer to answer instantly"* (Time and Study Environment) - *"It synthesises information from different lectures and resources, connecting them in ways I hadn't considered"* (Enhanced Comprehension and Information Management) - "*It cut down on team communication. Before, we'd work offline together on one computer. With ChatGPT, we'd share screens online—one person uses it while others do their own tasks, with less exchange"* (Teamwork and Communication) - *"With AI growing fast, you'll use tools like ChatGPT at work. Learning it in school builds job competitiveness"* (Workplace Readiness and Future Skills Development)	SRL: Self-Reflection (tool mindset); PBL: Build Knowledge (synthesis), Present Products (competitiveness)
Candidate 10	ChatGPT's role in Supporting SRL Components; Perceived Benefits of ChatGPT in PBL; Challenges and Limitations of ChatGPT Integration;	- *"quick answers on coding issues kept us engaged, unlike Google's dead ends that kill your mood"* (Self-Efficacy) - *"It suggested creative solutions I wouldn't have thought of myself, widening my perspective"* (Enhanced Creativity and Idea Generation) - *"It can't handle a high-level view of a big project" "it struggles with logical thinking, like how components or classes should work"* (Technical Limitation in Complex Task Management)	SRL: Performance (motivation, guidance); PBL: Project Launch (creativity), Build Knowledge (high-level planning)
Candidate 11	ChatGPT's role in Supporting SRL Components; Perceived Benefits of ChatGPT in PBL; Challenges and Limitations of ChatGPT	- *"pointed out a gap in my understanding of a function's logic. That pushed me to research it further, setting a goal to learn how it worked so I could improve the project"* (Metacognitive Self-Regulation) - *"like having someone to ask anytime, available 24/7"* (Help-Seeking, Always-Available Learning Support) - *"resolved specific coding issues quickly, keeping me on track"* (Time and Study Environment)	SRL: Performance (resolution, access), Self-Reflection (gap identification); PBL: Build Knowledge (tailored support), Develop & Critique

Participant ID	Key Themes Identifies	Supporting Evidence	Link to SRL Phases/PBL Elements
	Integration; Impact on Problem-Solving, Teamwork, and Communication Skills; Implications for Vocational Education Curricula	- *"Unlike a static textbook, ChatGPT tailors explanations to exactly what I'm struggling with"* (Personalised Guidance and Step-by-step Explanations) - "*Unlike teachers who have limited office hours, ChatGPT is always available when I'm actually working on assignments"* (Always-Available Learning Support) - *"When ChatGPT helps with debugging, it doesn't just say, 'Do this, it's fine.' It explains where you went wrong and how to fix it properly"* (Debugging and Error Resolution Support) - *"The main limitation is that it can't handle big projects well—you can't give it too much at once to organise, or it gets chaotic"* and "*With MVC's model and controller parts, there are too many components, and ChatGPT kept losing track or forgetting how to handle them, causing inconsistencies"* (Technical Limitation in Complex Task Management) - *"After this project, I realised communication is key. ChatGPT might suggest one direction, but teammates might be on different ones. Even with its suggestions, you need to focus on aligning everyone to one approach since it's a single project"* (Teamwork and Communication) - *"In the JSP project, the requirements were lengthy, and a clear summary early on would've saved us from messy revisions later"* (Personalised Learning Enhancement)	(communication, refinement)
Candidate 12	ChatGPT's Role in Supporting SRL Components; Perceived Benefits of ChatGPT in PBL; Challenges and Limitations of ChatGPT Integration; Implications for Vocational Education Curricula	- *"I do homework late, and when I hit problems then, they're tough to solve. Having ChatGPT available anytime is huge"* (Help-Seeking) - *"Knowing help is always available reduced my anxiety about getting stuck on difficult parts of the project"* (Always-Available Learning Support) - *"So, my motivation drops, and I don't try to understand as deeply on my own"* - *"But for reports, schools should watch out—it's too convenient, and students might just dump everything in there"* (Risk of Dependency and Reduced Learning Effort, Balancing AI Assistance with Independent Thinking) - *"It'd be great if it could give a learning plan when you ask a question"* and *"a plan suggesting which concepts to learn for specific project tasks would've guided my self-learning better"* (Personalised Learning	SRL: Performance (anxiety reduction, access); PBL: Build Knowledge (late support), Present Products (integrity concerns)

Participant ID	Key Themes Identifies	Supporting Evidence	Link to SRL Phases/PBL Elements
		Enhancement, Balancing AI Assistance with Independent Thinking)	
Candidate 13	ChatGPT's Role in Supporting SRL Components; Perceived Benefits of ChatGPT in PBL; Challenges and Limitations of ChatGPT Integration; Impact on Problem-Solving, Teamwork, and Communication Skills; Implications for Vocational Education Curricula	- *"students need the mindset that it's a tool, not a replacement for critical thinking"* (Control of Learning Belief, Pedagogical Strategies for Effective ChatGPT) - *"ChatGPT helped organise research findings and requirements into a cohesive structure for our project"* (Enhanced Comprehension and Information Management) - *"During brainstorming, ChatGPT offered multiple project approaches when we felt limited by our own ideas"* (Enhanced Creativity and Idea Generation) - *"Its answers aren't always 100% accurate, so we must verify with pros or online sources"* (Verification Requirements and Accuracy Concerns) - *"But long-term use might reduce human debugging opportunities. I could rely on it to fix bugs, which might limit my understanding of complex principles and create dependency"* and *"When I'm rushed or near a deadline, I might get lazy and ask ChatGPT to spit out the whole thing. I'd just take its answers instead of working through problems myself"* (Risk of Dependency and Reduced Learning Effort) - *"Before ChatGPT, we had much clearer, more defined divisions of work... With ChatGPT, the division isn't as extreme—it's less exaggerated"* (Teamwork and Communication) - *"it could offer more personalised learning—like tailoring resources to a user's progress, making it easier and reminding them what to focus on"* (Personalised Learning Enhancement) - *"It enhanced our learning and filled gaps, helping us understand the course material beyond just finishing the project"* (Enhanced Learning Outcomes Through ChatGPT) - *"Even when we got code from it, we often had to tweak it to fit. That meant we had to spend extra time re-explaining or reworking the code to align with the project"* (Verification Requirements and Accuracy Concerns) - *"It's about using it wisely—some excel with it, others misuse it and struggle. It depends on how you approach it"* (Balancing AI Assistance with Independent Thinking)	SRL: Self-Reflection (wise use, verification), Performance (organisation); PBL: Project Launch (brainstorming), Build Knowledge (learning enhancement)

Participant ID	Key Themes Identifies	Supporting Evidence	Link to SRL Phases/PBL Elements
Candidate 14	ChatGPT's Role in Supporting SRL Components; Perceived Benefits of ChatGPT in PBL; Challenges and Limitations of ChatGPT Integration; Implications for Vocational Education Curricula;	- *"before an exam, I had it quiz me, turning SRL into an interactive process"* (Metacognitive Self-Regulation) - *"By handling the basics quickly, I could spend more time on the creative and complex aspects of the assignment"* (Time Efficiency and Streamlined Learning) - *"The biggest issue is that sometimes you ask something, and it gives an answer or solution that's wrong. It can hallucinate—making up stuff that doesn't exist" and "Since it generates without verifying, if you don't know the topic well, you might trust it and mess up parts of the project"* and *"sometimes, project results are wrong because someone trusts ChatGPT's output as correct when it's not, increasing conflict chances"* (Verification Requirements and Accuracy Concerns) - *"some students copying answers directly for high marks"* and *"led some schools to ban AI last year"* (Risk of Dependency and Reduced Learning Effort) - *"integrating ChatGPT into PBL or other assignments"* and *"schools should proactively integrate ChatGPT and teach correct use"* (Curriculum Integration and Adaptation) - *"showing students how to use it as a tool rather than copying answers as their own"* (Pedagogical Strategies for Effective ChatGPT)	SRL: Performance (interactive process), Self-Reflection (trust issues); PBL: Develop & Critique (creativity), Project Launch (integration)
Candidate 15	ChatGPT's Role in Supporting SRL Components; Perceived Benefits of ChatGPT in PBL; Challenges and Limitations of ChatGPT Integration; Implications for Vocational Education Curricula; Impact on Problem-Solving, Teamwork, and	- *"I think even with ChatGPT, you need a base to use it well—it's not just handed to you. That base is what you've learned in the course, and ChatGPT pushes you further. I wouldn't say it stops me from learning—it enhances it"* (Control of Learning Belief) - *"Knowing I could quickly resolve issues with ChatGPT made the project feel less overwhelming"* and *"Even if I'm not great at coding, I don't have to avoid it—ChatGPT helps me contribute"* (Self-Efficacy) - *"when I hit a bug in the JSP project, getting a fast answer from ChatGPT kept me motivated to keep working"* (Self-Efficacy, Problem-Solving) - *"I could find relevant resources faster and fix bugs without spending hours searching, which let me focus on the core parts of the project"* (Time Efficiency and Streamlined Learning) - *"In the JSP project, I had a bug in my code that I couldn't trace. I gave ChatGPT the code, and it pointed out exactly where the issue was"* (Debugging and Error	SRL: Forethought (base knowledge), Performance (resolution, motivation), Self-Reflection (understanding); PBL: Build Knowledge (core focus, understanding), Develop & Critique (contribution)

Participant ID	Key Themes Identifies	Supporting Evidence	Link to SRL Phases/PBL Elements
	Communication Skills	Resolution Support, Problem-Solving) - *"with 1,000 lines of code in the JSP project, it couldn't handle tweaks or bug fixes in the later lines unless we manually broke it into smaller bits first"* (Technical Limitation in Complex Task Management) - *"I think even with ChatGPT, you need a base to use it well—it's not just handed to you"* (Critical Thinking) - *"In the JSP project, I could take on coding tasks I'd normally shy away from because ChatGPT provided guidance, spreading the load so everyone could pitch in more evenly"* (Teamwork and Communication) - *"If you ban AI completely, they'll be at a disadvantage like using mental math while others use calculators" and "Project-based learning mimics those settings, so welcoming AI makes sense for future jobs"* and *"in the JSP project, ChatGPT helped me contribute to coding tasks I wasn't strong in, preparing me for real-world scenarios where AI is common"* (Workplace Readiness and Future Skills Development) - *"in the JSP project, it helped me understand server connections better by explaining concepts I'd only partially grasped in class. That knowledge stuck with me, so I learned the material, not just finished the project"* (Enhanced Learning Outcomes Through ChatGPT)	
Candidate 16	Perceived Benefits of ChatGPT in PBL; Challenges and Limitations of ChatGPT Integration; Implications for Vocational Education Curricula; ChatGPT's Role in Supporting SRL Components	- *"I didn't just rely on it to finish—I used it to deepen my knowledge"* (Control of Learning Belief) - *"generate practice questions on server-side logic, which helped me identify gaps in my understanding and focus my learning on those areas"* (Metacognitive Self-Regulation) - *"when I was stuck on a JSP bug, ChatGPT's fast suggestion gave me confidence to keep going, making the project feel less daunting"* (Self-Efficacy) - *"It explains the whole process step by step, making it easier to follow than traditional resources"* (Personalised Guidance and Step-by-step Explanations) - *"It helped me think outside my usual patterns by suggesting unconventional but feasible approaches"* (Enhanced Creativity and Idea Generation) - *"Tasks that would take four hours were completed in one hour with ChatGPT's assistance"* (Time Efficiency and Streamlined Learning) - *"I don't fully trust it"* (Verification Requirements and	SRL: Performance (step-by-step, confidence), Self-Reflection (deepening, trust); PBL: Build Knowledge (practice questions, unconventional), Develop & Critique (curriculum shift)

Participant ID	Key Themes Identifies	Supporting Evidence	Link to SRL Phases/PBL Elements
		Accuracy Concerns) - *"I think I learned, but you need a base to use it well—it's not just given to you"* (Critical Thinking) - *"But the curriculum should shift too—focus on practical AI use instead of outdated methods" "It's like using a ballpoint pen instead of a quill"* (Curriculum Integration and Adaptation) - *"AI's the future, schools should teach students to use it sooner rather than later. Students need to understand how to wield it effectively to stay competitive"* (Workplace Readiness and Future Skills Development) - *"I didn't just rely on it to finish—I used it to deepen my knowledge, so I learned the material, not just completed the project"* (Enhanced Learning Outcomes Through ChatGPT)	