THE IMPACT OF THE USE OF ARTIFICIAL INTELLIGENCE TOOLS ON THE AUTONOMOUS LEARNING ABILITY OF HIGHER VOCATIONAL STUDENTS: A CASE STUDY OF NANJING VOCATIONAL COLLEGE OF ECONOMICS AND TRADE

ZHOU HONGREN
6617195707

AN INDEPENDENT STUDY SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF BUSINESS ADMINISTRATION
GRADUATE SCHOOL OF BUSINESS
SIAM UNIVERSITY
2025

THE IMPACT OF THE USE OF ARTIFICIAL INTELLIGENCE TOOLS ON THE AUTONOMOUS LEARNING ABILITY OF HIGHER VOCATIONAL STUDENTS: A CASE STUDY OF NANJING VOCATIONAL COLLEGE OF ECONOMICS AND TRADE

ZHOU HONGREN

This Independent Study Has Been Approved as a Partial Fulfillment of the Requirements for the Degree of Master of Business Administration

Advisor.......Ma Yu.......................
(Dr.MA YU)

Date: ....25...../.... ....6./...........2025

....

(Associate Professor Dr. Jomphong Mongkhonvanit)
Dean, Graduate School of Business

Date.........14...../...........1..../.........2026

Title: The Impact of the Use of Artificial Intelligence Tools on the Autonomous Learning Ability of Higher Vocational Students: A Case Study of Nanjing Vocational College of Economics and Trade

Researcher: Zhou Hongren

Degree: Master of Business Administration

Major: Educational Management

Advisor: ....Ma Yu....................

(Dr.MA YU)

..........25....../..........6........../......2025..........

ABSTRACT

As artificial intelligence (AI) tools become increasingly embedded in educational contexts, their influence on students' independent learning has gained scholarly attention. This study explored the impact of the use of artificial intelligence tools on the autonomous learning ability of students in higher vocational education, focusing on a case study of Nanjing Vocational College of Economics and Trade. Drawing upon the Technology Acceptance Model (TAM) and Self-Regulated Learning (SRL) theory, the research examined four key independent variables: prerequisite knowledge before using AI tools, difficulty in using AI tools, frequency of AI tool use, and process evaluation.

This study adopted quantitative research methodology, and a structured questionnaire was developed and distributed to 450 students, yielding 425 responses, of which 389 were valid. Using reliability and validity testing, descriptive statistics, correlation analysis, and multiple linear regression, the study found that prerequisite knowledge, frequency of use, and process evaluation positively and significantly influenced students' autonomous learning ability. In contrast, the difficulty of use did not have a significant effect.

The findings highlight the dual role of AI in supporting and potentially hindering student agency, suggesting that effective integration of AI tools in vocational education must be accompanied by appropriate guidance, training, and self-monitoring mechanisms. The study contributes to both theoretical understanding and practical strategies for enhancing autonomous learning in the age of intelligent technologies.

Keywords: artificial intelligence tools, autonomous learning ability, self-regulated learning

ACKNOWLEDGEMENT

I would like to express my deepest gratitude to my advisor for his invaluable guidance, support, and encouragement throughout my Independent Study. His insightful comments and constructive criticism have significantly improved the quality of my work.

Additionally, I am grateful to Associate Professor Dr. Jomphong Mongkhonvanit, Dean, Graduate School of Business, for his support and encouragement throughout my studies. His dedication to the graduate program and commitment to excellence have inspired me to strive for academic excellence.

Finally, I would like to extend my appreciation to all the faculty members and staff of Siam University who have contributed to my growth and development as a student. Their unwavering support and encouragement have been a source of inspiration and motivation to me.

Zhou Hongren

DECLARATION

I, Zhou Hongren, hereby declare that this Independent Study entitled "The Impact of the Use of Artificial Intelligence Tools on the Autonomous Learning Ability of Higher Vocational Students: A Case Study of Nanjing Vocational College of Economics and Trade" is an original work and has never been submitted to any academic institution for a degree.

(Zhou Hongren)
June 11, 2025

CONTENTS

LIST OF TABLES

LIST OF FIGURES

Chapter 1 Introduction

1.1 Background of the Study

In recent years, with the rapid development of generative artificial intelligence (AI), tools such as ChatGPT and DeepSeek have been widely integrated into educational settings. These AI tools provide students with convenient access to information, language assistance, and writing support, which can significantly improve learning efficiency. However, as AI becomes more embedded in students' daily academic practices, concerns have emerged about over-reliance on technology and its potential impact on essential learning abilities, particularly self-directed learning.

In the context of Chinese vocational colleges, many students come from educational backgrounds that emphasized rote memorization and exam-oriented learning. As a result, self-directed learning skills such as independent planning, time management, critical thinking, and problem-solving are often underdeveloped. Wang and Chen (2021) reported that nearly 95% of vocational college students had received minimal instruction in academic writing and research-based learning methods. Additionally, around 90% of students surveyed expressed that they lacked the time or motivation for independent study beyond class assignments. These findings reveal a significant gap between the demands of modern learning environments and the preparedness of vocational learners to navigate them autonomously.

At the same time, AI tools are increasingly viewed as double-edged swords in education. On one hand, they can serve as personalized learning assistants, helping students with tasks such as language translation, content generation, and topic exploration. This is particularly relevant in vocational education, where learners often face challenges in academic expression or have limited access to high-quality learning resources. On the other hand, frequent and uncritical use of AI tools may discourage deeper cognitive engagement. Students may begin to rely on AI-generated answers rather than processing information independently, reducing opportunities for critical thinking and reflective learning. According to Zhang et al. (2024), students who frequently use AI for academic tasks without sufficient self-monitoring are more likely to develop passive learning behaviors, decrease creativity, and lower levels of academic self-efficacy.

Moreover, vocational education has its own distinct characteristics that make the impact of AI even more complex. Many vocational courses emphasize hands-on skills, workplace readiness, and competency-based learning. AI tools can aid in these areas, for example, by simulating real-world scenarios, generating practice dialogues in service industries, or offering instant feedback on technical exercises. However, the effectiveness of these tools depends largely on how students use them. Without proper

AI literacy and guidance from instructors, students may use AI primarily as a shortcut rather than as a tool to deepen their understanding. This creates a challenge for educators: how to integrate AI effectively while ensuring that students continue to develop the self-directed learning skills, they need for lifelong success.

Additionally, the rise of process-based assessment in vocational education highlights the importance of learning processes, not just outcomes. If students bypass key steps in thinking or practice by relying on AI-generated outputs, their learning progress may be hindered despite good performance on final tasks. Therefore, understanding how AI tool dependency affects vocational students' learning behaviors and self-regulation is crucial for designing better teaching strategies and fostering meaningful learning experiences.

This study takes Nanjing Vocational College of Economics and Trade as a case to explore how students' prerequisite knowledge before using AI tools, frequency of AI usage, perceived difficulty of AI tools, and process evaluation relate to their autonomous learning ability. The findings aim to provide empirical evidence for optimizing AI integration in vocational education and contribute to the broader discussion on educational equity, digital competency, and student-centered pedagogy in the age of artificial intelligence.

1.2 Questions of the Study

As artificial intelligence (AI) tools such as ChatGPT and DeepSeek are rapidly integrated into educational environments, students are now able to access information, get real-time help, and generate content faster. While these tools have brought many benefits, especially in terms of learning efficiency, they have also raised some important questions: how do these technologies affect students' autonomous learning ability? In vocational education, students need to develop both technical skills and autonomous learning abilities, so it is particularly important to understand the reliance on AI.

Based on the theory of self-regulated learning and the educational evaluation theory, this study proposes the following research questions:

1.What is the effect of students' prerequisite knowledge before using AI tools on their autonomous learning ability?

2.What is the effect of the difficulty in using AI tools on students' autonomous learning ability?

3.What is the effect of the frequency of use of AI tools on students' autonomous learning ability?

4.What is the effect of process evaluation on students' autonomous learning ability in the context of AI-supported learning?

1.3 Objectives of the Study

To explore the interaction between AI tool usage and students' learning autonomy in vocational education, this study adopts Self-Regulated Learning Theory and Educational Evaluation Theory as its theoretical framework. The objectives of this research are:

1.To examine the impact of students' prerequisite knowledge before using AI tools on their autonomous learning ability in AI-supported learning environments.

2.To examine the impact of the difficulty in using AI tools on students' autonomous learning ability in AI-supported learning environments.

3.To examine the impact of the frequency of AI tool use on students' autonomous learning ability in AI-supported learning environments.

4.To examine the impact of process evaluation on students' autonomous learning ability in AI-supported learning environments.

1.4 Scope of the Study

This study took the students of Nanjing Vocational College of Economics and Trade as the main research subjects, and the survey subjects were vocational students who are studying in the school and have experience in using artificial intelligence tools. Participants must have used AI tools such as ChatGPT, DeepSeek, etc. at least once or more in learning scenarios, and have a basic understanding and evaluation of the tool's operating experience and its impact on their learning behavior.

The data collection for this survey was mainly through online and offline questionnaire surveys. To ensure that most students could participate, we collected a list of students willing to participate in the survey through the student union of the school and used a random sampling method to randomly select 450 students from the list as research samples. The survey distributed 450 questionnaires from January 15, 2025, to May 15, 2025, and 425 were collected.

1.5. Significance of the Study

1.5.1 Theoretical Significance

With the rapid integration of artificial intelligence into education, AI tools have become increasingly effective in enhancing learning efficiency and improving access to resources. However, existing research mainly focuses on the functional aspects of AI and its instructional applications, with limited attention to its deeper influence on students' learning behaviors, particularly their self-directed learning abilities. In vocational education, students' learning motivation, planning capabilities, and sustained learning skills are crucial for their future professional development. Therefore, it is especially important to systematically examine how reliance on AI tools affects these competencies. This study aims to fill this gap by analyzing the shifts in self-directed learning ability and its influencing mechanisms under the usage of AI tools. The findings are expected to enrich theoretical contributions at the intersection of educational technology and learning behavior, providing a novel theoretical basis for AI-supported educational evaluation and student competence development.

1.5.2 Practical Significance

This study takes Nanjing Vocational College of Economics and Trade as a case to empirically investigate the current use of AI tools in real teaching contexts and their specific impact on students' self-directed learning behavior. The results will offer practical insights for vocational colleges to guide students in the appropriate use of AI tools and to prevent excessive reliance during teaching reforms. The findings can help institutions and educators optimize instructional design by not only improving learning efficiency but also preserving students' critical thinking and learning initiative. Furthermore, the study encourages the formation of a hybrid learning model that combines "AI-assisted support" with "self-driven internalization," ultimately promoting the all-round development of students' core competencies in vocational education. These insights can also inform policy recommendations for integrating AI into vocational curricula and teacher training programs.

1.6 Definition of Key Terms

1.6.1 Prerequisite Knowledge Before Using AI Tools

This refers to the basic knowledge or general learning ability a student has before starting to use AI tools. The depth and relevance of this background knowledge affects how students understand, interpret, and apply AI-generated content. Students with stronger knowledge reserves are often better able to critically assess and integrate AI outputs into their learning process, supporting their autonomous learning development.

1.6.2 Difficulty in Using AI Tools

This variable captures students' perceived level of difficulty when operating AI tools. It includes user interface complexity, clarity of system responses, usability challenges, and the cognitive effort required for effective use. High perceived difficulty may discourage engagement and hinder the development of independent learning strategies, while low difficulty can facilitate smoother integration into self-directed learning routines.

1.6.3 Frequency of Use of AI Tools

This refers to how often students utilize AI tools during their learning activities, typically categorized by daily, weekly, or monthly usage. The frequency not only reflects students' familiarity with AI but also signals their degree of reliance on such tools. High-frequency users may benefit from efficiency gains but also face risks of reduced self-regulation if over-reliant.

1.6.4 Process Evaluation

Process evaluation involves the assessment of students' learning procedures, including task planning, progress monitoring, and reflective revision, rather than solely the final product. In AI-supported learning, this kind of formative evaluation encourages students to engage in deeper cognitive processes and maintain responsibility for their own learning progress, thereby enhancing their autonomous learning ability.

1.6.5 Autonomous Learning Ability

Autonomous learning ability is the capacity of learners to initiate, manage, and evaluate their own learning without external control. It involves skills such as goal-setting, time management, self-motivation, and self-assessment. Within vocational education, this ability is crucial for adapting to dynamic work environments and pursuing lifelong learning.

1.6.6 AI Tool Dependency

AI tool dependency is defined as the extent to which students rely on AI applications to complete academic tasks, solve problems, or make learning decisions. While moderate use may enhance productivity and engagement, excessive reliance can lead to superficial understanding, reduced cognitive effort, and weakened self-directed learning skills.

Chapter 2 Literature Review

2.1 Prerequisite Knowledge Before Using AI Tools

Prerequisite knowledge before using AI tools refers to the foundational skills, digital literacy, and conceptual understanding that learners must possess in order to effectively engage with artificial intelligence technologies in educational settings. This includes familiarity with basic computer operations, understanding of how AI tools function, and the cognitive ability to critically interpret and apply AI-generated outputs. The presence or absence of such foundational knowledge significantly influences students' readiness to adopt and integrate AI into their learning processes (Baker & Smith, 2019).

According to the Self-Regulated Learning (SRL) theory, learners with sufficient prior knowledge are more capable of planning, monitoring, and evaluating their own learning (Zimmerman, 2002). When applying AI tools, students need to set learning goals, input meaningful prompts, interpret responses, and decide how to integrate the information into their assignments or study strategies. Without adequate prior knowledge, students may misuse AI tools, accept incorrect outputs, or fail to understand how to refine queries for better results (Khan, 2023).

Vocational education students often have diverse educational backgrounds and varying levels of digital literacy. Studies have shown that students with strong ICT (Information and Communication Technology) skills are more confident and autonomous when using AI platforms (Ng, 2012). In contrast, those lacking foundational knowledge tend to rely on AI tools passively, which could lead to surface learning or dependency rather than deeper engagement (Tang & Zhou, 2023).

Furthermore, prerequisite knowledge includes understanding ethical considerations when using AI. Students must be aware of the potential for bias, misinformation, and plagiarism when relying on AI-generated content (Floridi et al., 2018). Educators play a vital role in guiding learners on responsible AI use and embedding critical digital literacy into the curriculum to ensure students develop a balanced and reflective approach to using AI tools (Tsai et al., 2020).

Training programs and onboarding sessions that introduce students to AI concepts, functionalities, and best practices can significantly improve learning outcomes. Research by Qian and Clark (2022) highlights that when students are equipped with even minimal instruction about how AI tools work and how to interact with them effectively, they are more likely to engage in metacognitive strategies and show higher levels of motivation.

In summary, prerequisite knowledge is a crucial determinant of students’ ability to benefit from AI tools. Without it, students may misuse or misunderstand the technology, leading to poor learning outcomes and reduced autonomy. Institutions should therefore prioritize the development of AI-related foundational knowledge, especially in vocational education contexts where disparities in digital readiness may be more pronounced.

2.2 Difficulty in Using AI Tools

The difficulty in using AI tools refers to the perceived complexity and usability barriers students encounter when interacting with artificial intelligence platforms, particularly in educational contexts. This factor is critical in understanding students' behavioral intention, acceptance, and subsequent learning outcomes. According to the Technology Acceptance Model (TAM), perceived ease of use is a major determinant of user acceptance (Davis, 1989). In the context of AI in education, if students find tools too complicated or unintuitive, they may avoid using them altogether or use them inefficiently, which can hinder their learning progress and affect their autonomous learning development.

Usability issues often arise from a lack of AI literacy, ambiguous outputs, or insufficient guidance. For instance, Zhang et al. (2023) reported that many students in Chinese vocational institutions expressed confusion about how to interact with AI chatbots such as ChatGPT, especially when prompts required precise language or iterative refinement. These difficulties can result in frustration or cognitive overload, which negatively affects learners' engagement and autonomy (Sweller et al., 2011).

In addition, the user interface design of AI tools plays a key role in perceived difficulty. Tools with unclear functions or complicated settings may discourage effective usage (Park, 2009). In contrast, intuitive and user-friendly interfaces have been linked to higher levels of engagement and learning satisfaction (Chen et al., 2021). This is particularly relevant in vocational education, where students may have limited digital literacy or experience with advanced technologies.

Another factor influencing difficulty perception is the language of instruction and platform accessibility. Many AI tools are developed primarily in English, which can be a barrier for non-native speakers (Lee & Hsieh, 2019). This linguistic gap can complicate students' interpretation of AI-generated content and reduce their confidence in using the tools independently. A study by Chan and Hu (2023) found that students expressed concerns about the accuracy and clarity of AI-generated content, particularly when it did not align with their linguistic and cultural contexts.

Students' prior experiences and individual learning styles also affect how difficult they perceive AI tools to be. Some students with prior programming or technical knowledge may find AI tools easier to use (Sun, 2022). while others with weaker digital skills may struggle with command inputs, interpreting responses, or integrating the results into their assignments (Li & Zheng, 2023). In a study by Tang and Zhou (2023), vocational students who received basic AI training were more confident and effective in utilizing AI tools, suggesting that perceived difficulty can be mitigated through targeted instruction.

Moreover, the cognitive demands of AI tools often require higher-order thinking, such as critically evaluating AI outputs, rephrasing queries, and synthesizing results. Without proper training or scaffolding, students may find these tasks difficult, leading to surface learning or dependency on AI-generated responses without deeper understanding (Rahimi & Shute, 2021).

Recent research also highlights the emotional factors linked to perceived difficulty. If students feel overwhelmed or anxious when using AI tools, they may associate negative emotions with learning, further reducing their willingness to explore independently. A study by Pitts et al. (2025) revealed that students' concerns about overreliance on AI tools and the potential loss of critical thinking skills contributed to their apprehension in using such technologies.

To address these challenges, scholars advocate for embedded guidance, simplified interfaces, and context-based training in AI tool usage (Wang et al., 2023). Educators must ensure that AI technologies are accompanied by instructional support and aligned with learners' digital competence levels. This is especially important in vocational settings, where students may vary greatly in terms of technological readiness and learning preferences.

In conclusion, the difficulty in using AI tools is a significant barrier that can affect how students engage with technology, manage their learning, and develop autonomy. Reducing perceived difficulty through better design, instruction, and support can enhance students' motivation, confidence, and self-regulated learning behaviors in AI-assisted environments.

2.3 Frequency of Use of AI Tools

The frequency of using AI tools is a vital indicator of how students engage with artificial intelligence in academic environments. It not only reflects their familiarity and dependency on these tools but also acts as a proxy for technology adoption and integration into everyday learning routines. A higher frequency of use is generally associated with improved academic performance, stronger digital competence, and the development of autonomous learning behaviors (Venkatesh & Davis, 2000).

Recent studies have highlighted a sharp rise in the regular use of AI-based educational tools. For instance, Liu et al. (2023) found that over 70% of university students reported using AI-powered applications—such as ChatGPT, Grammarly, and DeepL—multiple times per week. This frequent engagement fosters skills acquisition, boosts motivation, and enhances confidence in managing digital resources Krause et al. (2024). However, the effectiveness of such usage depends not only on frequency but also on the quality and intent behind interactions with AI systems (van der Kleij et al., 2015).

From the Self-Regulated Learning (SRL) perspective, frequent use of AI tools facilitates the development of metacognitive strategies. These include goal setting, time management, and self-monitoring of academic tasks (Panadero, 2017). Students who regularly use AI for feedback or content generation often exhibit autonomous learning behaviors such as drafting revisions, refining queries, and verifying outputs (Zhang & Wang, 2023). This aligns with findings by Green and Chen (2020), who reported that habitual AI users tend to engage in more iterative and reflective learning cycles.

On the flip side, high-frequency use may sometimes result in over-reliance. Li and Chen (2022) noted that students excessively dependent on AI tools risk diminishing their critical thinking abilities and may develop an "automation bias," relying on AI outputs without adequate scrutiny. This can hinder the development of foundational knowledge and reduce learning authenticity.

The frequency of AI tool use is also shaped by institutional and cultural factors. Educational environments that encourage the use of AI technologies through policies, infrastructure, and training programs tend to report higher student engagement (Alghamdi & Aldossari, 2021). Conversely, students in institutions with limited access or poor digital literacy support tend to use AI tools less frequently.

Student characteristics such as prior experience, digital literacy, and confidence also influence usage frequency. Those with a background in technology or high perceived competence are more likely to integrate AI tools regularly into their study habits (Teo, 2011). Motivational variables, including perceived usefulness, ease of use, and peer influence, further determine engagement levels (Holmes et al., 2021).

Demographics such as age and gender may also affect usage patterns. Research shows that younger students and male learners are typically more experimental and receptive to new AI tools (Sánchez-Prieto et al., 2019), although this gender gap has narrowed with the widespread availability of digital learning platforms.

Another emerging dimension concerns ethical awareness. As AI use becomes more routine, students must also be educated about potential misuse, such as plagiarism, bias, or overuse. Holmes et al. (2021) emphasized the importance of embedding ethical AI literacy into curricula to mitigate the risks of high-frequency AI use.

In conclusion, the frequency of AI tool usage is a multifaceted construct encompassing opportunity and caution. While regular engagement promotes familiarity, self-regulation, and academic support, excessive or uncritical use may hinder independent learning. Educational institutions should encourage intentional, ethical, and pedagogically sound use of AI through training, accessibility, and policy integration.

2.4 Process Evaluation

Process evaluation plays a central role in educational research, particularly in understanding how interventions—such as the use of AI tools—are implemented and experienced by learners. While outcome evaluation focuses on results, process evaluation emphasizes how learning occurs, including the quality, fidelity, and responsiveness of the educational experience (Patton, 2008). In the context of AI-supported learning, evaluating the learning process is essential to ensure that technology facilitates not just faster but deeper and more reflective learning (Ifenthaler & Yau, 2020).

Process evaluation in AI-enhanced education typically examines the stages through which students engage with content and tools. According to Kirkpatrick and Kirkpatrick (2006), process evaluation includes indicators like learner engagement, interaction with the AI system, adaptability, and feedback integration. AI tools can record and analyze learning logs, providing granular insights into how students interact with learning materials over time (Zawacki-Richter et al., 2019).

One key benefit of AI in process evaluation is the ability to offer adaptive feedback. Studies show that when learners receive timely, personalized feedback through intelligent systems, they are more likely to self-correct and develop metacognitive awareness (Gikandi et al., 2011). For example, intelligent tutoring systems (ITS) track student behavior, highlight misconceptions, and provide step-by-step guidance—all of which are crucial for formative assessment (VanLehn, 2011).

Moreover, process evaluation is tied closely to formative assessment and self-regulated learning (SRL). Zimmerman (2002) noted that monitoring learning progress is a key phase in SRL models. AI tools support this by enabling students to assess their own learning through visualizations, dashboards, or progress indicators (Lu et al., 2018). When students are aware of their learning processes, they are more likely to adjust strategies and improve outcomes.

Another vital element is engagement metrics, such as time on task, tool usage patterns, and frequency of feedback requests. These data points offer meaningful indicators of learning quality and help educators adjust instructional strategies accordingly (Scheffel et al., 2014). For instance, a study by Roll and Winne (2015) demonstrated that students who frequently engaged with reflective prompts and AI feedback showed significant gains in deep learning compared to those with passive tool usage.

However, challenges remain. Process data collected from AI systems can be overwhelming, leading to concerns about data overload and the validity of interpretation (Reimann, 2009). Educators and researchers must interpret behavioral indicators carefully, considering contextual factors such as motivation, prior knowledge, and cognitive load (Winne & Baker, 2013).

Ethical concerns also arise in AI-supported process evaluation. Transparent algorithms, student consent, and data privacy are key considerations in designing responsible AI interventions (Holmes et al., 2021). Without ethical safeguards, process monitoring can feel intrusive and reduce students' intrinsic motivation.

Importantly, vocational education, such as at Nanjing Institute of Industry and Trade, places emphasis on practical skill development. Here, process evaluation supported by AI can bridge the gap between theoretical instruction and real-world application. Tools such as AI-powered simulations, virtual labs, and skill trackers offer real-time insights into students' procedural learning (Kühnlenz et al., 2021).

In conclusion, process evaluation provides a nuanced lens to assess the dynamics of AI-facilitated learning. It not only informs pedagogical improvement but also empowers students to become reflective, self-directed learners. The integration of AI in process evaluation must be deliberate, ethical, and aligned with learners' developmental goals.

2.5 Autonomous Learning Ability

Autonomous learning ability refers to students' capacity to take initiative, set learning goals, monitor progress, and evaluate outcomes without constant external guidance. In the context of AI-assisted education, this ability plays a pivotal role in determining whether students use AI tools as a supplement to enhance their learning or become overly dependent on them (Zimmerman, 2002).

According to the Self-Regulated Learning (SRL) theory, autonomous learners engage in proactive strategies such as goal setting, self-monitoring, and self-reflection, which are essential for effective interaction with AI tools (Panadero, 2017). These students are more likely to evaluate AI-generated outputs critically, revise prompts strategically and use the tools to deepen understanding rather than merely complete tasks. Conversely, students with weak autonomous learning abilities may accept AI responses without verification, leading to shallow learning or misinformation (Rahimi & Shute, 2021).

The use of AI tools in education can both support and challenge the development of autonomous learning. On one hand, AI can act as a personalized tutor, offering tailored feedback and resources that foster independence (Chen et al., 2021). On the other hand, if learners lack metacognitive skills or confidence, they may rely excessively on AI-generated content, by passing essential thinking processes such as analysis and synthesis (Zawacki-Richter et al., 2019).

Vocational students often exhibit varying levels of autonomous learning, depending on their prior education, motivation, and learning habits. Research by Liu and Wang (2022) found that students with higher digital literacy and self-efficacy were more likely to use AI tools constructively, while those without these attributes tended to engage in copy-paste behaviors or unquestioned acceptance of results.

Moreover, emotional and psychological factors—such as motivation, academic confidence, and anxiety—can also affect autonomous learning. Students who feel empowered by AI tools may develop greater confidence and curiosity, whereas those overwhelmed by unfamiliar technologies may avoid experimentation and remain passive (Lee, 2021). Thus, fostering a growth mindset and providing adequate training are essential for developing learners' autonomy in AI-enhanced environments.

Instructors can promote autonomous learning by integrating AI tools into problem-solving tasks, reflection journals, and formative assessments that encourage active thinking and self-evaluation. Scaffolding strategies, such as modeling how to critique AI outputs or refining prompts, can also gradually transfer responsibility from teacher to learner (Hadwin et al., 2018).

In summary, autonomous learning ability is not only a prerequisite for effective use of AI tools but also an outcome that can be strengthened through their strategic integration. Enhancing students' self-regulated learning skills is essential for maximizing the educational potential of AI while minimizing dependency risks.

2.6 Conceptual Framework

According to this research model, the variables involved include independent variables and dependent variable. The independent variables are prerequisite knowledge before using AI tools, difficulty in using AI tools, frequency of use of AI tools and process evaluation, and the dependent variable is autonomous learning ability. Based on the research results at home and abroad, this study draws on the theory of self-regulated learning (SRL) and the educational evaluation theory to explore the impact of the use of artificial intelligence tools on the autonomous learning ability of vocational education students. It is assumed that there is a positive relationship between them and autonomous learning ability. The relationship diagram is as follows:

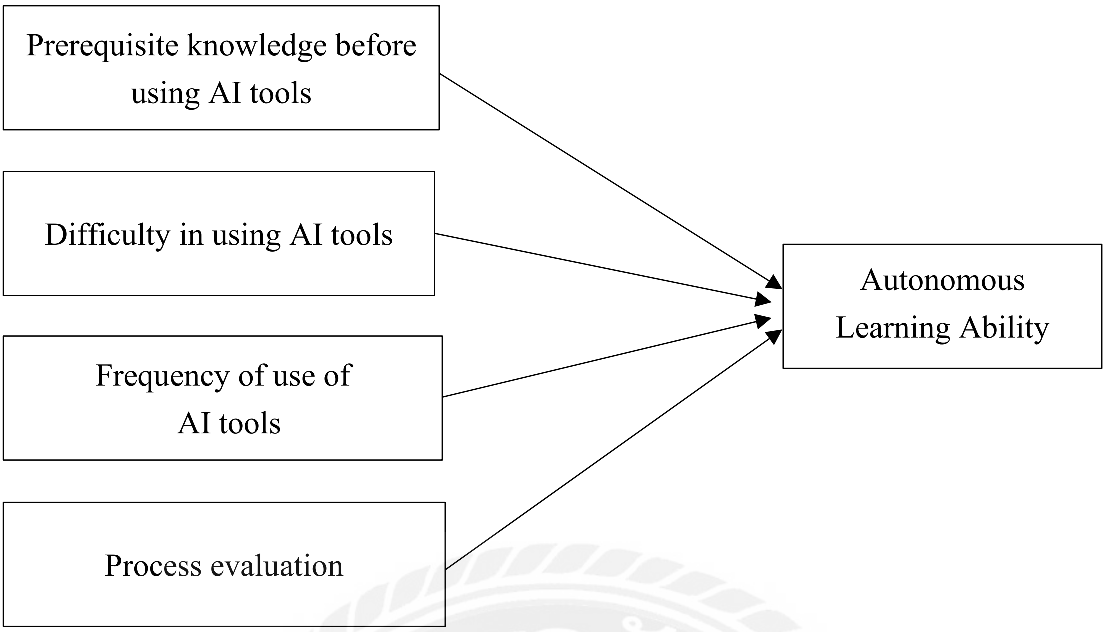

Figure 2.1 Conceptual Framework

chapter 3 Research Methodology

3.1 Research Design

This study adopted a quantitative research design to investigate the influence of AI tool usage on vocational students' autonomous learning ability at Nanjing Institute of Industry and Technology. The questionnaire survey method was used to collect data, consisting of items measured with a 5-point Likert scale.

This approach allows for structured data collection and statistical analysis, providing insights into the relationships between independent variables—prerequisite knowledge before using AI tools, difficulty in using AI tools, frequency of use of AI tools, and process evaluation—and the dependent variable—autonomous learning ability. The research design aligns with the conceptual framework and theoretical foundations introduced in Chapter 2, particularly Self-regulated Learning Theory and Educational Evaluation Theory.

3.2 Population and Sample

The target population of this study consisted of full-time students at Nanjing Institute of Industry and Technology during the 2024–2025 academic year. To ensure broad participation, the research team collaborated with the university's Student Union to collect a list of students who voluntarily agreed to participate in the study. A simple random sampling method was employed to select 450 students from the list as the research sample.

3.3 Research Hypotheses

Based on the research objectives and literature review, the following hypotheses were proposed to examine the relationships among the key variables. All hypotheses assume positive correlations between the independent variables and the dependent variable:

H1: Prerequisite knowledge before using AI tools is positively associated with students' autonomous learning ability.

H2: Difficulty in using AI tools is positively associated with students' autonomous learning ability.

H3: Frequency of use of AI tools is positively associated with students' autonomous learning ability.

H4: Process evaluation of the use of AI tools is positively associated with students' autonomous learning ability.

3.4 Research Instrument

This study used a structured questionnaire as the main data collection tool to investigate the influence of AI tool use on vocational students' autonomous learning ability. The questionnaire design was grounded in relevant theories and literature, focusing on five key dimensions: prerequisite knowledge before using AI tools, difficulty in using AI tools, frequency of use of AI tools, process evaluation, and autonomous learning ability. Each item was rated on a five-point Likert scale (1 = strongly disagree to 5 = strongly agree), capturing students' perceptions of their AI usage behaviors and self-regulated learning ability.

The first part of the questionnaire collected demographic information, including gender, year of study, major, and the primary purpose of using AI tools. The second part focused on the hypothesized variables and included 28 items across the five dimensions mentioned above. The questionnaire was distributed both online and offline. Data was collected, screened, and analyzed to examine the relationships between AI tool usage and students' autonomous learning ability.

Table 3.1 Questionnaire Items

Dimension	Items
Prerequisite knowledge before using AI tools AI	1.Before using AI tools (such as ChatGPT) to assist learning, I have a certain amount of basic knowledge about the topic/task I want to learn.
	2.I can clearly understand the core concepts involved in the answers or suggestions generated by the AI tool.
	3.Before asking questions to the AI tool, I usually know what specific problem I need to solve.
	4.I have the basic knowledge background to evaluate whether the information provided by the AI tool is accurate and reliable.
Difficulty in using AI tools	1.I find it easy to learn and master how to use AI tools (e.g., input valid instructions and understand output).
	2.I can skillfully use appropriate instructions (prompt) to let AI tools generate the answers or content I need.
	3.Compared with using other learning tools (e.g., search engines, library databases), I find it easier and more convenient to use AI tools.
	4.I rarely encounter technical obstacles or operational difficulties when using AI tools.
Frequency of use of AI tools	1.I often use AI tools when completing homework or tasks assigned by the teacher.

	2.When I preview or review course content, I will actively use AI tools to help understand.
	3.When I encounter learning difficulties, I tend to use AI tools first or often to seek answers or ideas.
	4.During independent learning time (not required by class), I use AI tools frequently.
	5. I often try to use different AI tools to meet different learning needs.
Process evaluation	1.When using AI tools to learn, I will focus on how I think and solve problems step by step (not just the final answer).
	2.I will reflect on the logic and reasoning behind the answers or suggestions provided by the AI tools.
	3.When the answers given by the AI tools are not ideal, I will analyze the reasons and try to adjust my questioning style or thinking.
	4.I will use the feedback from the AI tools to evaluate my understanding and progress in the learning process.
	5.Even with the assistance of AI tools, I also focus on cultivating my ability to think independently and explore solutions.
Autonomous learning ability	1.I can set clear and specific learning goals for myself.
	2.I can develop an effective learning plan based on my learning goals and situation.
	3.I can actively find and use various learning resources (including but not limited to AI tools) to solve learning problems.
	4.When I encounter difficulties in the learning process, I can actively try different strategies to overcome them.
	5.I can monitor my learning progress and understanding and adjust my learning strategies as needed.
	6. I can evaluate the effectiveness of my learning and reflect on the strengths and weaknesses of the learning process.
	7.I am responsible for my own learning and do not need too much external supervision.
	8.I can think critically about information and do not blindly accept answers from AI tools or other sources.

	9.I have a sustained interest and motivation to learn new knowledge and skills.
	10.I can identify errors or imperfections in the answers given by AI tools and make corrections or supplements.

3.5 Reliability and Validity Analysis of the Scale

3.5.1 Reliability Analysis

Reliability analysis was conducted to assess the internal consistency of the questionnaire. This study used SPSS 26.0 to perform reliability analysis on each dimension. Cronbach's Alpha coefficient was used as the evaluation index. A coefficient above 0.8 is generally considered to indicate high reliability.

The questionnaire includes four independent variables—prerequisite knowledge before using AI tools, difficulty in using AI tools, frequency of use of AI tools, and process evaluation—as well as the dependent variable—autonomous learning ability. The reliability results are shown in Table 3.2 below:

Table 3.2 Reliability Analysis

	Cronbach's Alpha	Number of Items
Prerequisite knowledge before AI tools	0.821	4
Difficulty in using AI tools	0.804	4
Frequency of use of AI tools	0.835	5
Process evaluation	0.864	5
Autonomous learning ability	0.889	10
Overall Scale	0.925	28

The Cronbach's Alpha coefficients of all dimensions exceed 0.8, indicating that the internal consistency of the measurement items is high and the questionnaire has good reliability.

3.5.2 Validity Analysis

Validity analysis was conducted to test whether the questionnaire accurately reflects the research objectives. This study used the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test of sphericity to evaluate the structural validity of the questionnaire.

As shown in Table 3.3, the KMO value is 0.872 (>0.8), and Bartlett's test is significant ($p < 0.001$), indicating that the questionnaire data are suitable for factor analysis and that the overall scale has good validity.

Table 3.3 Validity Analysis

KMO and Bartlett's Test	
Test Item	Value
KMO Sampling Suitability Measure	0.872
Bartlett’s Approx. Chi-Square	4619.615
Degrees of Freedom	210
Significance (p-value)	0.000

3.6 Data Collection

This study collected data through a structured questionnaire survey administered to students at Nanjing Vocational College of Economics and Trade from January 15 to May 15, 2025. The questionnaire was distributed both online and offline via the college’s official student communication channels. A total of 450 questionnaires were distributed, and 389 valid responses were obtained after screening, yielding a valid response rate of 86.4%. The screening process ensured that only participants with AI tool usage experience and complete responses were included in the final dataset.

The criteria for valid responses were as follows:

1.All questionnaire items were fully completed.

2.The completion time met the minimum quality control threshold.

3.Respondents confirmed that they had used AI tools in their learning processes.

These measures ensured the reliability and validity of the data used in this study.

3.7 Data Analysis

The collected data were analyzed using SPSS 26.0. Descriptive statistics were used to summarize demographic information and responses for each variable. To explore the relationships between the four independent variables—prerequisite knowledge before using AI tools, difficulty in using AI tools, frequency of use of AI tools, and process evaluation—and the dependent variable—autonomous learning ability, Pearson correlation analysis and multiple linear regression analysis were conducted. Statistical significance was set at the 0.05 level.

Chapter 4 Findings and Discussion

4.1 Findings

4.1.1 Demographic Characteristics of Respondents

A total of 389 valid questionnaires were collected in this study. The demographic distribution of the respondents is summarized in Table 4.1.

Table 4.1 Demographic Characteristics of Respondents

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	181	46.5%
	Female	208	53.5%
Year of Study	Freshman	96	24.7%
	Sophomore	171	44.0%
	Junior	122	31.3%
Major	Economics & Management	135	33.9%
	Liberal Arts	81	20.8%
	Science & Engineering	108	27.8%
	Arts & Design	68	17.5%
Main Purpose of AI Tool Usage	Search for information	245	63.0%
	Solving academic problems	218	56.0%
	Assignment/ paper writing	201	51.7%
	Language learning/translation	166	42.7%
	Creative writing	92	32.6%
	Programming/ code assistance	74	19.0%

The data show that female students slightly outnumbered male students. Most respondents were in their sophomore or junior year, and the dominant majors were Economics & Management and Science & Engineering. Regarding the purpose of using AI tools, the most common reasons were searching for information, solving academic problems, and completing assignments or reports.

4.1.2 Descriptive Statistics of Key Variables

Descriptive statistics were conducted to understand the overall distribution of responses for each variable. Table 4.2 presents the mean and standard deviation of each dimension.

Table 4.2 Descriptive Statistics of Key Variables

Variable	Number of Items	Mean	Std. Deviation
Prerequisite knowledge before AI tools	4	3.61	0.72
Difficulty in using AI tools	4	3.45	0.81
Frequency of use of AI tools	5	3.76	0.68
Process evaluation	5	3.84	0.70
Autonomous learning ability	10	3.59	0.75
Note: Multiple responses allowed for AI usage purposes.			

The results indicate that students rated their frequency of AI tool use and process evaluation relatively high, while prerequisite knowledge and autonomous learning ability were slightly lower but moderate overall.

4.1.3 Correlation Analysis

To explore the relationships between variables, Pearson correlation analysis was conducted. Table 4.3 shows the correlation coefficients for the four independent variables and the dependent variable—autonomous learning ability.

Table 4.3 Pearson Correlation Coefficients

Variable	1	2	3	4	5
1. Prerequisite knowledge before AI tools	1				
2. Difficulty in using AI tools	.421**	1			
3. Frequency of use of AI tools	.389**	.456**	1		
4. Process evaluation	.435**	.472**	.493**	1	
5. Autonomous learning ability	.462**	.407**	.498**	.534**	1
Note: $p < 0.01$ (2-tailed)					

All independent variables showed a significant positive correlation with autonomous learning ability, with process evaluation having the highest correlation ($r = .534$).

This suggests that students who frequently reflect on their learning process are more likely to demonstrate autonomous learning behaviors.

4.1.4 Regression Analysis

A multiple linear regression analysis was conducted to examine how the four independent variables jointly influence autonomous learning ability. The regression model is summarized in Table 4.4.

Table 4.4 Multiple Linear Regression Analysis

Variable	Unstandardized B	Standardized Beta	t-value	Sig.
Prerequisite knowledge before AI tools	0.213	0.208	4.271	0.000
Difficulty in using AI tools	0.127	0.112	2.437	0.015
Frequency of use of AI tools	0.196	0.198	4.031	0.000
Process evaluation	0.285	0.273	5.328	0.000
$R^2 = 0.412$, Adjusted $R^2 = 0.407$				

The model explains 41.2% of the variance in autonomous learning ability (Adjusted $R^2 = 0.407$). All four independent variables have a statistically significant positive impact, with process evaluation being the strongest predictor.

4.2 Interpretation of Findings

This study proposed four hypotheses to examine the impact of AI tool usage on students' autonomous learning ability. The results of the regression analysis confirmed that all four independent variables have a significant positive influence on the dependent variable—autonomous learning ability.

H1: Prerequisite knowledge before using AI tools is positively associated with students' autonomous learning ability.

This hypothesis was supported. The results show that students with stronger foundational knowledge tend to better interpret and apply AI-generated content, leading to more independent learning. This aligns with Zimmerman's (2002) self-regulated learning theory, which emphasizes the role of prior knowledge in learning autonomy.

H2: Difficulty in using AI tools is positively associated with students' autonomous learning ability.

This hypothesis was also supported, though the influence was relatively weaker compared to other variables. It suggests that when students overcome initial difficulties in using AI tools, they may develop stronger problem-solving and self-regulation skills.

This finding resonates with Sweller's cognitive load theory, indicating that manageable challenge can foster engagement and autonomy.

H3: Frequency of use of AI tools is positively associated with students' autonomous learning ability.

This hypothesis was supported. Frequent users were more familiar with AI operations, which enhanced their ability to manage tasks, revise outputs, and seek feedback. This supports the view of Panadero (2017) that regular practice with learning tools promotes metacognitive development.

H4: Process evaluation is positively associated with students' autonomous learning ability in the context of AI-supported learning.

This was the most influential factor among the four. Students who consistently reflected on their learning process and actively engaged with AI feedback showed significantly stronger autonomous learning behavior. This reinforces the argument by Ifenthaler and Yau (2020) that process-based assessment fosters deeper learning and critical thinking.

Overall, the findings validate that AI tools, when used actively and critically, can support the development of self-directed learning skills among vocational students. However, the positive effects depend on students' digital literacy, engagement strategies, and ability to reflect on learning tasks.

4.3 Comparison with Previous Research

The results of this study are largely consistent with prior research on self-regulated learning and AI-supported education.

First, the positive impact of prerequisite knowledge before using AI tools on autonomous learning ability supports findings by Zimmerman (2002), who emphasized that learners with sufficient prior knowledge are better equipped to plan, monitor, and evaluate their own learning. Similarly, Khan (2023) noted that foundational understanding is essential for interpreting and integrating AI-generated content effectively.

Second, although difficulty using AI tools had a weaker influence, it still showed a significant relationship with learning autonomy. This aligns with Sweller et al. (2011) cognitive load theory, which suggests that moderate difficulty can stimulate cognitive engagement. Tang and Zhou (2023) also observed that students with basic AI training felt more confident and self-directed when using intelligent systems.

Third, the role of frequency of use of AI tools as a positive predictor confirms the findings of Panadero (2017) and Zhang & Wang (2023), who reported that frequent engagement with learning technologies promotes the development of metacognitive strategies. Green and Chen (2020) similarly found that students who habitually used AI tools were more reflective and iterative in their learning processes.

Most notably, process evaluation emerged as the most influential factor in promoting autonomous learning. This echoes the work of Ifenthaler and Yau (2020), who emphasized the role of formative assessment and adaptive feedback in fostering deep learning. Gikandi et al. (2011) also found that real-time feedback and progress tracking enhance learners' self-awareness and independent learning behaviors.

These results suggest that while AI tools offer substantial support for vocational students, their effectiveness depends on how students engage with the tools. Responsible, reflective, and skill-aligned use of AI can bridge learning gaps, especially in environments where students may lack prior training in autonomous learning.

Thus, the study reinforces and extends prior findings in the vocational education context.

4.4 Unexpected Results

While the overall findings were consistent with expectations, a few observations merit further reflection. Notably, the variable difficulty in using AI tools, although statistically significant, showed the weakest influence on autonomous learning ability among the four independent variables. This result contrasts with previous studies (e.g., Zhang et al., 2023; Rahimi & Shute, 2021) that emphasized usability barriers as major obstacles to effective learning engagement.

One possible explanation is that most respondents in this study had already adapted to AI tools through repeated use in daily learning, reducing the perceived difficulty over time. It is also possible that students who initially found the tools difficult simply used them less frequently, which diluted the variable's explanatory power in the regression model.

Another point worth noting is that while prerequisite knowledge was positively associated with learning autonomy, its effect size was less pronounced than expected. This may reflect the fact that many vocational students rely more on practice-based and interactive learning styles, and less on theoretical foundations when using AI tools. In such contexts, frequency of use and reflective engagement (as captured by process evaluation) may play a more central role in shaping learning outcomes.

Lastly, despite the overall positive associations, the R^2 value of 0.412 indicates that over half of the variation in autonomous learning ability remains unexplained by the four variables examined. This suggests that other factors—such as learning motivation, teacher guidance, or peer influence—may also significantly affect students' ability to learn independently in AI-supported environments. These aspects should be further explored in future research.

These unexpected outcomes underline the need to explore additional psychological and contextual factors in future AI-supported learning research.

Chapter 5 Conclusion and Recommendation

5.1 Conclusion

This study investigated the impact of artificial intelligence (AI) tool use on the autonomous learning ability of higher vocational students, using Nanjing Vocational College of Economics and Trade as a case study. Grounded in the theoretical frameworks of self-regulated learning and educational evaluation, the research focused on four independent variables—prerequisite knowledge before using AI tools, difficulty in using AI tools, frequency of use of AI tools, and process evaluation—and examined their effects on the dependent variable, autonomous learning ability.

A quantitative research design was employed, and data were collected through a structured questionnaire distributed to students with prior experience using AI tools in academic contexts. A total of 389 valid responses were analyzed using SPSS 26.0, incorporating descriptive statistics, Pearson correlation analysis, and multiple linear regression.

The findings reveal that all four independent variables exerted a significant and positive influence on students' autonomous learning ability. Process evaluation emerged as the most powerful predictor, highlighting the critical role of reflective learning and formative assessment in AI-enhanced educational environments. Frequency of use of AI tools also had a strong positive association, suggesting that regular engagement helps students develop confidence, digital competence, and self-regulated learning behaviors. Prerequisite knowledge before using AI tools was found to facilitate deeper understanding and critical application of AI-generated content, thereby supporting more independent learning. Although difficulty in using AI tools showed the weakest effect, it still contributed meaningfully, indicating that overcoming initial operational challenges may enhance students' learning persistence and self-efficacy.

In conclusion, this study provides empirical support for the argument that AI tools, when appropriately used, can act as catalysts for improving autonomous learning among vocational college students. Rather than replacing independent thought, AI-assisted learning environments can—if properly guide students to plan, monitor, and evaluate their learning more actively. These findings offer valuable insights for educational practitioners and policymakers seeking to integrate AI technologies into vocational education while preserving and promoting core learner competencies. They also contribute to the growing body of research linking digital tool usage with self-regulated learning theory in practice-oriented educational settings.

5.2 Recommendation

Drawing upon the empirical findings of this study, the following recommendations are offered for students, instructors, and vocational institutions to better integrate AI tools into the learning process while preserving and enhancing students' autonomous learning ability.

1. For Students: Promote Conscious and Reflective Use of AI Tools

Students should be explicitly encouraged to engage with AI tools not just for results, but for learning process support. For example, when using ChatGPT or DeepSeek, learners should actively reflect on how the AI's responses were generated and verify their correctness before accepting or applying them.

It is important that students develop the habit of setting clear learning goals before using AI tools, instead of depending on them for direction. Goal setting is a core part of autonomous learning, and AI should not support this process.

Students may also benefit from maintaining a learning log or reflection journal while using AI tools, recording how the output was used, what was learned, and whether their understanding improved. This can strengthen their process evaluation ability.

2. For Teachers: Provide Structured AI Literacy and Learning Strategy Guidance

Instructors should incorporate AI tool tutorials and prompt-crafting guidance into their teaching. Students often utilize AI due to a lack of knowledge on how to ask effective questions or refine inputs.

Teachers can design scaffolded assignments that explicitly require students to reflect on AI usage (e.g., "What did AI suggest? What did you accept or reject, and why?"), thus embedding process evaluation in everyday tasks.

Teachers should also differentiate instruction based on students' prerequisite knowledge. For those with weaker foundations, additional guidance or group work may be necessary to prevent blind reliance on AI tools.

3. For Vocational Colleges: Build Institutional Mechanisms for Balanced AI Integration

Institutions should develop clear guidelines on ethical and educational use of AI, outlining both capabilities and limitations. These can help students avoid plagiarism and misuse.

Assessment frameworks should be adjusted to include formative elements, such as learning journals, progress reviews, and prompt refinement reports, to assess not only outcomes but also learning autonomy and process awareness.

Colleges are encouraged to establish digital learning support centers or help desks that offer regular workshops on effective AI use tailored to different majors (e.g., business report writing with AI, technical translation, etc.).

For students with high dependency and low process engagement, schools could offer self-regulated learning enhancement programs, integrating digital tools and peer support to gradually build learning independence.

In summary, improving autonomous learning ability in the AI era requires coordinated efforts at the student, teacher, and institutional levels. The effective use of AI tools in vocational education should not only enhance task efficiency, but also cultivate habits of critical thinking, metacognitive reflection, and goal-oriented learning. These recommendations can serve as actionable steps for integrating AI into teaching and learning practices in a way that promotes both technological fluency and learner autonomy.

These multi-level efforts can help vocational learners use AI tools more strategically while preserving critical learning autonomy.

5.3 Further Study

Although this study provides meaningful insights into the relationship between AI tool usage and autonomous learning ability among vocational students, several limitations should be acknowledged, which may serve as directions for future research.

First, the study was conducted at a single institution, Nanjing Vocational College of Economics and Trade, which may limit the generalizability of the findings. Future studies could expand the sample to include multiple vocational colleges across different regions, disciplines, or levels to explore whether institutional or cultural differences influence the observed relationships.

Second, the research relied solely on self-reported questionnaire data, which may introduce subjective bias. Respondents may overestimate their use of AI tools or their actual level of autonomous learning. Future research may benefit from combining self-report instruments with behavioral data, such as AI usage logs, learning analytics, or performance assessments, to obtain a more comprehensive and objective understanding.

Third, the current study examined only four independent variables. Other factors—such as teacher support, peer influence, digital access, motivation, and academic anxiety—were not included but may significantly affect students' autonomous learning development. Future studies should explore additional psychological and contextual factors, and may also investigate how these variables interact with AI tool use to produce long-term learning outcomes.

Fourth, this study adopted a cross-sectional design. As AI usage habits and self-regulated learning skills develop over time, future research should consider longitudinal designs to track how students' AI tool use and learning behaviors evolve across semesters or academic years.

Lastly, the study focused on the general use of AI tools in learning. Future research may examine domain-specific AI use cases, such as how students in accounting, hospitality, or design programs apply AI differently, and how this shapes their self-directed learning pathways.

This study lays the foundation for future empirical and theoretical exploration of AI-assisted learning in vocational education. More studies in this area will help educators better understand how to use AI tools wisely—both to improve learning outcomes and to support students' independent learning development in vocational settings.

References

Alghamdi, A., & Aldossari, H. (2021). Exploring digital readiness and barriers to AI integration in higher education. *Education and Information Technologies*, 26(5), 5453–5472. https://doi.org/10.1007/s10639-021-10590-1

Baker, T., & Smith, L. (2019). *Educ-AI-tion rebooted? Exploring the future of artificial intelligence in schools and colleges*. Nesta. https://www.nesta.org.uk/report/education-rebooted/

Chen, W., Looi, C. K., & Chen, L. (2021). Integrating AI into education: A framework for effective usage and learning autonomy. *Educational Technology & Society*, *24*(3), 1–12.

Chan, C. K. Y., & Hu, W. (2023). *Students' voices on generative AI: Perceptions, benefits, and challenges in higher education*. arXiv preprint arXiv:2305.00290. https://arxiv.org/abs/2305.00290

Chen, W., Looi, C. K., & Chen, W. (2021). Understanding engagement and satisfaction in AI-supported learning environments. *Educational Technology & Society*, *24*(3), 1–13.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319–340. https://doi.org/10.2307/249008

Floridi, L., Cowls, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V., ... & Vayena, E. (2018). AI4People—An ethical framework for a good AI society: Opportunities, risks, principles, and recommendations. *Minds and Machines*, *28*(4), 689–707. https://doi.org/10.1007/s11023-018-9482-5

Gikandi, J. W., Morrow, D., & Davis, N. E. (2011). Online formative assessment in higher education: A review of the literature. *Computers & Education*, 57(4), 2333–2351. https://doi.org/10.1016/j.compedu.2011.06.004

Green, C., & Chen, L. (2020). Automation bias and the implications for learning with intelligent systems. *Technology, Knowledge and Learning*, 25(2), 345–360. https://doi.org/10.1007/s10758-019-09428-3

Holmes, W., Bialik, M., & Fadel, C. (2021). *Artificial intelligence in education: Promises and implications for teaching and learning*. Center for Curriculum Redesign. https://curriculumredesign.org/publications/

Hadwin, A. F., Järvelä, S., & Miller, M. (2018). Self-regulated, co-regulated, and socially shared regulation of learning. In D. H. Schunk & J. A. Greene (Eds.), *Handbook of self-regulation of learning and performance* (2nd ed., pp. 83–106). Routledge.

Holmes, W., Bialik, M., & Fadel, C. (2021). Ethics of AI in education: Towards a community-wide framework. *Journal of Artificial Intelligence in Education*, 31(1), 1–15. https://doi.org/10.1007/s40593-021-00239-1

Ifenthaler, D., & Yau, J. Y. K. (2020). Utilising learning analytics to support study success in higher education: A systematic review. *Educational Technology Research and Development*, 68(4), 1961–1990. https://doi.org/10.1007/s11423-020-09788-z

Kirkpatrick, D. L., & Kirkpatrick, J. D. (2006). *Evaluating training programs: The four levels* (3rd ed.). Berrett-Koehler.

Kühnlenz, F., Weber, D., & Klumpp, M. (2021). Smart vocational education and training (VET) using virtual reality and AI: Requirements for learning process evaluation. *Procedia Computer Science*, 192, 3942–3951. https://doi.org/10.1016/j.procs.2021.09.183

Krause, S., Panchal, B. H., & Smith, J. (2024). Evolution of learning: Assessing the transformative impact of generative AI on higher education. *ResearchGate*. https://www.researchgate.net/publication/391568347

Khan, S. (2023). Understanding AI prompt engineering and student readiness: An exploratory study. *Journal of Educational Computing Research*, *61*(1), 25–42.

Li, Y., & Chen, L. (2022). The effects of over-reliance on AI dialogue systems on students' cognitive abilities. *Smart Learning Environments*, 9(1), 1–15. https://doi.org/10.1186/s40561-022-00189-6

Liu, X., Qiu, H., & Sun, Y. (2023). Exploring students' patterns of AI tool usage and its relationship with academic self-efficacy. *British Journal of Educational Technology*, 54(2), 321–337. https://doi.org/10.1111/bjet.13277

Lu, O. H. T., Huang, A. Y. Q., Huang, J. C. H., & Yang, S. J. H. (2018). Applying learning analytics for the early prediction of students' academic performance in blended learning. *Educational Technology & Society*, 21(2), 220–232.

Lee, M.-C., & Hsieh, C.-T. (2019). Usability and effectiveness of English-language AI learning systems for non-native speakers. *Journal of Educational Computing Research*, *57*(8), 2034–2056.

Li, H., & Zheng, Y. (2023). The role of digital literacy in vocational students' adoption of AI technologies. *International Journal of Educational Technology in Higher Education*, *20*(1), 18.

Lee, M. (2021). Student agency and autonomous learning in technology-rich environments. *British Journal of Educational Technology*, *52*(4), 1532–1547. https://doi.org/10.1111/bjet.13104

Liu, X., & Wang, H. (2022). Examining vocational students' AI use and learning behaviors: The role of digital self-efficacy. *Journal of Vocational Education Research*, *45*(2), 110–127.

Ng, W. (2012). Can we teach digital natives digital literacy? *Computers & Education*, *59*(3), 1065–1078. https://doi.org/10.1016/j.compedu.2012.04.016

Park, S. Y. (2009). An analysis of the technology acceptance model in understanding university students' behavioral intention to use e-learning. *Educational Technology & Society*, *12*(3), 150–162.

Patton, M. Q. (2008). *Utilization-focused evaluation* (4th ed.). SAGE Publications.

Panadero, E. (2017). A review of self-regulated learning: Six models and four directions for research. *Frontiers in Psychology*, *8*, 422. https://doi.org/10.3389/fpsyg.2017.00422

Pitts, G., Marcus, V., & Motamedi, S. (2025). *Student perspectives on the benefits and risks of AI in education*. arXiv preprint arXiv:2505.02198. https://arxiv.org/abs/2505.02198

Qian, Y., & Clark, R. (2022). *Design and validation of an AI literacy questionnaire: The affective, cognitive, and metacognitive dimensions*. British Journal of Educational Technology. Advance online publication. https://doi.org/10.1111/bjet.13411

Qian, Y., & Clark, R. (2022). Enhancing student engagement with AI learning tools: The role of initial training and perceived competence. *Educational Technology Research and Development*, *70*(2), 471–487. https://doi.org/10.1007/s11423-021-10009-0

Rahimi, M., & Shute, V. J. (2021). Enhancing learning with AI: The impact of cognitive and metacognitive scaffolding. *Educational Psychologist*, *56*(4), 208–225. https://doi.org/10.1080/00461520.2021.1956939

Reimann, P. (2009). Time is precious: Variable- and event-centred approaches to process analysis in CSCL research. *International Journal of Computer-Supported Collaborative Learning*, 4(3), 239–257. https://doi.org/10.1007/s11412-009-9070-z

Rahimi, M., & Shute, V. J. (2021). The role of critical thinking and self-regulated learning in using AI tools for education. *Journal of Educational Psychology*, *113*(4), 694–707.

Roll, I., & Winne, P. H. (2015). Understanding, evaluating, and supporting self-regulated learning using learning analytics. *Journal of Learning Analytics*, 2(1), 7–12. https://doi.org/10.18608/jla.2015.21.2

Sun, Y. (2022). The influence of technical background on students' AI tool proficiency. *Computers & Education*, *182*, 104474.

Sweller, J., Ayres, P., & Kalyuga, S. (2011). *Cognitive load theory*. Springer.

Scheffel, M., Drachsler, H., Stoyanov, S., & Specht, M. (2014). Quality indicators for learning analytics. *Educational Technology & Society*, 17(4), 117–132.

Sánchez-Prieto, J. C., Olmos-Migueláñez, S., & García-Peñalvo, F. J. (2019). Gender differences in the acceptance of AI tools in education. *Computers in Human Behavior*, 92, 341–349. https://doi.org/10.1016/j.chb.2018.11.021

Tang, J., & Zhou, X. (2023). The impact of AI literacy training on vocational students' learning behavior. *Asia-Pacific Journal of Educational Technology*, *32*(2), 145–160.

Tsai, Y. S., Poquet, O., Gašević, D., Dawson, S., & Pardo, A. (2020). Complexity leadership in learning analytics: Drivers, challenges and opportunities. *British Journal of Educational Technology*, *51*(6), 1206–1225. https://doi.org/10.1111/bjet.12946

Tsai, M.-J., Poquet, O., Gašević, D., Dawson, S., & Pardo, A. (2020). *Conceptualizing AI literacy: An exploratory review*. Computers and Education: Artificial Intelligence, 1, Article 100003. https://doi.org/10.1016/j.caeai.2020.100003

Teo, T. (2011). Factors influencing teachers' intention to use technology: Model development and test. *Computers & Education*, 57(4), 2432–2440. https://doi.org/10.1016/j.compedu.2011.06.008

VanLehn, K. (2011). The relative effectiveness of human tutoring, intelligent tutoring systems, and other tutoring systems. *Educational Psychologist*, 46(4), 197–221. https://doi.org/10.1080/00461520.2011.611369

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science*, 46(2), 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926

van der Kleij, F. M., Feskens, R. C. W., & Eggen, T. J. H. M. (2015). Effects of feedback in a computer-based learning environment on students' learning outcomes: A meta-analysis. *Review of Educational Research*, 85(4), 475–511. https://doi.org/10.3102/0034654314564881

Wang, Y., Liu, J., & Huang, R. (2023). Designing AI-supported learning environments for vocational education: A practical framework. *British Journal of Educational Technology*, *54*(1), 89–107.

Wang, L., & Chen, Y. (2021). *Challenges in cultivating self-directed learning among vocational college students in China*. Journal of Vocational Education and Practice, 34(2), 45–58.

Winne, P. H., & Baker, R. S. (2013). The potentials of educational data mining for researching metacognition, motivation, and self-regulated learning. *JEDM—Journal of Educational Data Mining*, 5(1), 1–8.

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education: Opportunities and challenges. *International Journal of Educational Technology in Higher Education*, *16*(1), 1–27. https://doi.org/10.1186/s41239-019-0171-0

Zimmerman, B. J. (2002). Becoming a self-regulated learner: An overview. *Theory into Practice*, *41*(2), 64–70. https://doi.org/10.1207/s15430421tip4102_2

Zhang, Q., Li, H., & Xu, M. (2024). *The influence of generative AI on students' learning behavior: Opportunities and risks*. International Journal of Educational Technology, 41(1), 22–37.

Zhang, L., Yu, X., & Li, M. (2023). Barriers to effective AI tool usage among vocational students in China. *Journal of Computer Assisted Learning*, *39*(1), 112–126. https://doi.org/10.1111/jcal.12722

Zhang, H., & Wang, X. (2023). AI tools in vocational education: Enhancing student engagement and deep learning. *Journal of Educational Technology & Society*, 26(3), 45–58.

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education– where are the educators? *International Journal of Educational Technology in Higher Education*, 16(1), 1–27. https://doi.org/10.1186/s41239-019-0171-0

Appendix

Questionnaire

Appendix: Survey on the Impact of Artificial Intelligence Tool Use on Autonomous Learning Ability of Higher Vocational Students

Dear Sir or Madam,

I am a graduate student at Siam University, and I am studying the Impact of the use of artificial lntelligence tools on autonomous learning ability of vocational college students. This research meets the requirements of my Master of Management degree program.

Please assist me in completing this study by filling out the following questionnaire.

The information you share today will be used solely for this study and academic purposes. Please select the option that best reflects your actual situation.

Completing the questionnaire will take approximately 15-20 minutes. Please read each question carefully to ensure the research's scientific reliability. Your participation is crucial to the success of this study.

I want to thank you for your response! If you have any questions, don't hesitate to contact me at the Email: 1241006013@qq.com.

Zhou Hongren, Graduate. student

Siam University

Part 1 Questionnaire

1. Demographic information Remark:

Please choose using ✓ in ☑ or fill data in the blank.

01. Gender:

☐Male ☐Female

02.Year of Study:

☐Freshman ☐Sophomore ☐Junior

03.Major:

☐Liberal Arts ☐Science ☐Engineering

☐Economics & Management ☐Arts

04.Primary purpose(s) of using AI tools: *(Multiple choices allowed)*

☐Searching learning materials/information

☐Solving academic questions/problems

☐Completing assignments/reports/papers

☐Language learning/translation

☐Programming/coding assistance

☐Creative writing/brainstorming

☐Image/video generation

2.Relational factors.

For many of the sections, we deploy the widely acknowledged "5-point Likert scale" ranging from "Completely not compliant" (scored as 1) to "Completely compliant" (scored as 5). Intermediate scores represent varying degrees of conformity or nonconformity.

Dimension	Items	1	2	3	4	5
Prerequisite knowledge before using AI tools AI	1.Before using AI tools (such as ChatGPT) to assist learning, I have a certain amount of basic knowledge about the topic/task I want to learn.					
	2.I can clearly understand the core concepts involved in the answers or suggestions generated by the AI tool.					
	3.Before asking questions to the AI tool, I usually know what specific problem I need to solve.					
	4.I have the basic knowledge background to evaluate whether the information provided by the AI tool is accurate and reliable.					
Difficulty in using AI tools	1.I find it easy to learn and master how to use AI tools (e.g., input valid instructions and understand output).					
	2.I can skillfully use appropriate instructions (prompt) to let AI tools generate the answers or content I need.					
	3.Compared with using other learning tools (e.g., search engines, library					

	databases), I find it easier and more convenient to use AI tools.					
	4.I rarely encounter technical obstacles or operational difficulties when using AI tools.					
Frequency of use of AI tools	1.I often use AI tools when completing homework or tasks assigned by the teacher.					
	2.When I preview or review course content, I will actively use AI tools to help understand.					
	3.When I encounter learning difficulties, I tend to use AI tools first or often to seek answers or ideas.					
	4.During independent learning time (not required by class), I use AI tools frequently.					
	5. I often try to use different AI tools to meet different learning needs.					
Process Evaluation	1.When using AI tools to learn, I will focus on how I think and solve problems step by step (not just the final answer).					
	2.I will reflect on the logic and reasoning behind the answers or suggestions provided by the AI tools.					
	3.When the answers given by the AI tools are not ideal, I will analyze the reasons and try to adjust my questioning style or thinking.					
	4.I will use the feedback from the AI tools to evaluate my understanding and progress in the learning process.					
	5.Even with the assistance of AI tools, I also focus on cultivating my ability to think independently and explore solutions.					

Autonomous Learning Ability	1.I can set clear and specific learning goals for myself.					
	2.I can develop an effective learning plan based on my learning goals and situation.					
	3.I can actively find and use various learning resources (including but not limited to AI tools) to solve learning problems.					
	4.When I encounter difficulties in the learning process, I can actively try different strategies to overcome them.					
	5.I can monitor my learning progress and understanding and adjust my learning strategies as needed.					
	6. I can evaluate the effectiveness of my learning and reflect on the strengths and weaknesses of the learning process.					
	7.I am responsible for my own learning and do not need too much external supervision.					
	8.I can think critically about information and do not blindly accept answers from AI tools or other sources.					
	9.I have a sustained interest and motivation to learn new knowledge and skills.					
	10.I can identify errors or imperfections in the answers given by AI tools and make corrections or supplements.					