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Adopting AI-powered chatbots for academic performance: A qualitative model based on grounded theory approach

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ABSTRACT

Artificial intelligence (AI) integration into higher education is expanding. This study aims to conceptualise the higher vocational lecturers' adoption of AI-powered chatbots (AIPC) for academic performance. This research employs semi-structured interviews to collect data from 30 lecturers across 10 Chinese higher vocational higher education institutes. And then, using grounded theory to process the data. The findings reveal that AI-powered chatbot adoption is shaped by institutional support, pedagogical adaptability, and social influence. Institutional support, including leadership commitment, policy incentives, and structured training, plays a decisive role. Pedagogical adaptability varies across disciplines, with humanities and management lecturers more receptive than engineering and technical instructors, who highlight AI's limitations in hands-on training. Social influence in higher vocational education is multi-tiered, shaped not only by peers and students but also by institutional leadership and industry collaborations. Finally, this research develops a qualitative model to encourage adopting AI-powered chatbots for academic performance.

Keywords: Artificial intelligence (AI), chatbots, higher vocational education, technology adoption, institutional support.

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INTRODUCTION

Academic performance is of paramount importance to faculty members in higher education institutions, as it directly influences promotion, career advancement, and the production and impact of scholarly research. In the digital era, the enhancement of academic performance has transcended traditional approaches and increasingly relies on the support of intelligent technologies, particularly the application of artificial intelligence (AI). In recent years, AI technology has been increasingly integrated into higher education, not only optimizing teaching methodologies but also providing substantial support in research management, data analysis, and academic writing. This integration enables faculty members to conduct academic activities more efficiently, thereby improving research output and teaching quality. With the continuous advancement of AI, its applications in higher education have expanded beyond basic automated assessment to include intelligent teaching support and academic research assistance across multiple domains. This transformation is reshaping the teaching and research landscape in higher education, positioning AI-driven academic tools as a critical means of enhancing academic performance (Abulibdeh et al., 2024; Bearman et al., 2023; Hooda et al., 2022; Mahoney et al., 2021; Sajja et al., 2024).

In higher education, the integration of AI technology is driving substantial transformations in teaching methodologies and academic management. AI-driven intelligent tutoring systems provide personalized learning recommendations, automated assessment tools improve grading efficiency, and AI-assisted text analysis tools support academic writing and research (Halkiopoulos and Gkintoni, 2024). Additionally, AI-powered chatbots have gained increasing attention in recent years, being applied in classroom interactions, knowledge inquiry, automated teaching management, and research assistance (Chen et al., 2023). By leveraging AI chatbots, educators can more effectively organize course content, respond to student inquiries, and optimize educational resource allocation. However, despite the promising advantages of AI technology in higher education, its adoption still faces several challenges. The adoption of AI in higher education varies significantly across institutions, with disparities in technological infrastructure, faculty training, and actual implementation (Chan, 2023).

The use of AI-powered chatbots for academic performance from high-quality university lecturers is prominent, because they have access to robust digital infrastructure and regular training, and are well-positioned to harness AI-powered chatbots for both teaching and research. For higher vocational institutions lecturers, which have fewer outdated systems and resources, limiting their ability to innovate and fully participate in academic research. However, the acceptance of AI-powered chatbots in higher vocational institutions is still problematic, with the reasons including limited technology and a skeptical attitude towards the perception that AI-based Chatbots are largely non-interactive that do not meet work's needs (Al-khresheh, 2024; Kirkby et al., 2023; Shah et al., 2024).

As of 2024, there are 11133 higher vocational education institutions in China. The Chinese government and educational authorities have implemented policies to support technological integration and pedagogical innovation in higher vocational education institutions. As of 2024, 24 provinces (autonomous regions and municipalities) have announced a total future investment of RMB 48.6 trillion. The area of artificial intelligence and industrial Internet and education information technology applications is included in the new infrastructure. Higher vocational education lecturers face systemic barriers, such as inadequate access to digital tools, limited institutional support for technological integration, and a shortage in technological adaptability, and the skill-based nature of vocational curricula (Ali et al., 2024; Lin et al., 2024; Mei and Symaco, 2022; Wu et al., 2022). Hence this study aims to develop a conceptual framework to foster AI-powered chatbots for academic performance.

After the introduction, section two provides a literature review, summarizing the current research on AI applications in higher education, discussing relevant technology acceptance theories, and identifying the key challenges faced by higher vocational education lecturers in AI adoption. Section three outlines the research methodology, detailing the qualitative research design, data collection, and analytical procedures. Section four presents the research findings, analyzing lecturers' perceptions, adoption experiences, and the key challenges and opportunities associated with AI-powered chatbots. Finally, Section five discusses the implications of the findings and provides theoretical and practical insights for future research and policy development.

LITERATURE REVIEW

AI chatbots

AI chatbots, designed to simulate human-like interaction through natural language processing, have garnered significant attention in various domains. These systems facilitate real-time dialogue, offering tailored support and information to users, thereby positioning themselves as trans-formative tools in the education sector. By engaging learners through personalized interactions, AI chatbots aim to enhance learning experiences and outcomes (Ahmad et al., 2022; Casheekar et al., 2024).

Current research on AI chatbots predominantly focuses on their applications in domains such as healthcare, business, and customer service. For instance, studies have explored their role in extending cognitive-behavioral therapies and improving accessibility to healthcare services. Similarly, in business, they serve as customer service agents, capable of handling repetitive tasks and providing efficient solutions, thus reducing operational burdens and improving customer satisfaction. These studies have largely examined themes of user engagement, technological design, and ethical considerations, emphasizing their usability and potential limitations (Luo et al., 2022; Wang et al., 2024; Xu et al., 2021).

Research exploring the application of AI chatbots in higher vocational education for lecturers' academic performance sector remains limited. While some studies highlight their use for student-centered purposes, such as tutoring, feedback provision, and administrative assistance, their influence on lecturers—particularly in enhancing teaching outcomes and academic performance—has received insufficient scholarly attention (Chen et al., 2023; Dahri et al., 2024). This is especially evident in higher vocational education, where lecturers encounter unique challenges in integrating technology into curricula and pedagogy.

Figure 1 shows that most papers are published in education and educational research, various subfields of psychology, and computer science. It indicates a significant emphasis on understanding the educational impact of AI chatbots, their psychological effects on users, and advancements in their technical development.

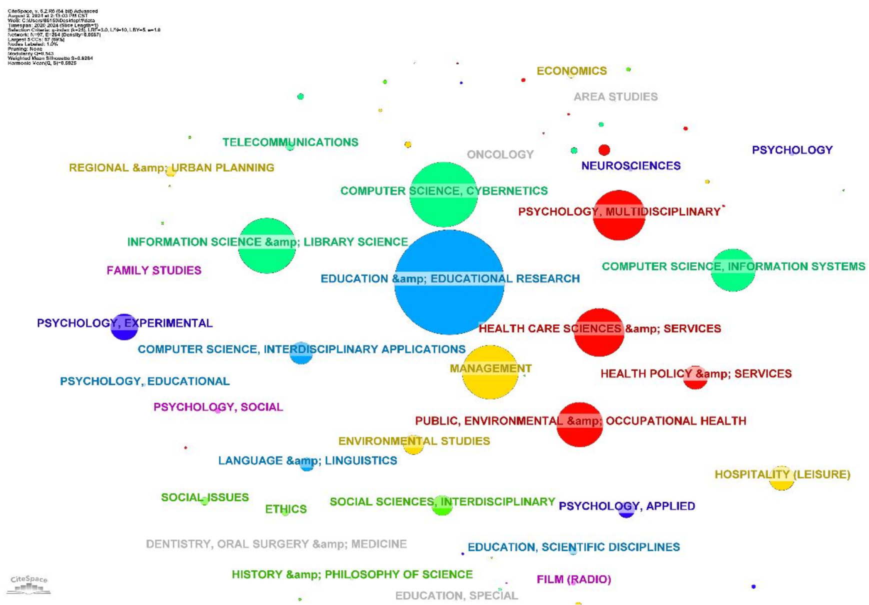

Figure 1. The maps of categories in AI chatbots.

Academic performance

Academic performance encompasses multiple facets of an academic's professional responsibilities, including teaching, research, and administrative contributions (Reymert and Thune, 2023). As a critical indicator of institutional excellence, it is often closely tied to the reputation and standing of universities, influencing faculty promotion, salary increments, and tenure decisions (Pontika et al., 2022). Academic performance reflects their contributions to teaching, research, and service, forming a critical basis for evaluations and strategic goals within academic institutions.

Figure 2 illustrates the top 17 keywords with the strongest citation bursts in research from 2020 to 2024, showcasing topics that experienced significant increases in academic attention over specific periods. The keywords on academic performance are limited.

Top 17 Keywords with the Strongest Citation Bursts

Keywords	Year	Strength	Begin	End	2020 - 2024
innovation performance	2020	4.57	**2020**	2021	
trends	2020	4.57	**2020**	2021	
dynamics	2020	3.35	**2020**	2021	
computer	2020	3.35	**2020**	2021	
company	2020	3.26	**2020**	2021	
prevalence	2020	3.04	**2020**	2021	
performance evaluation	2020	3.04	**2020**	2021	
ivory tower	2020	3.04	**2020**	2021	
developing country	2020	2.74	**2020**	2021	
business performance	2020	2.62	**2020**	2021	
level	2020	2.43	**2020**	2021	
organizational change	2020	2.43	**2020**	2021	
associations	2020	2.43	**2020**	2021	
sleep quality	2020	2.43	**2020**	2021	
cell phone use	2020	2.13	**2020**	2021	
ict	2020	2.02	**2020**	2021	
circular economy	2021	3.91	**2021**	2022	

Figure 2. Top 17 keywords on AI chatbots for performance.

AI chatbots in higher education sectors

The application of artificial intelligence (AI) in higher education has significantly expanded, encompassing teaching, academic management, and research support. AI-driven technologies are increasingly utilized to facilitate intelligent course management, automated assessment, academic writing assistance, and student engagement. These advancements have enhanced efficiency and accessibility in educational settings, paving the way for broader integration of AI tools in higher education. Technology acceptance model (TAM) and unified theory of acceptance and use of technology (UTAUT) have extensively explored faculty and student acceptance of AI technologies, which have identified perceived usefulness, and social influence as key determinants of AI adoption. However, most of these studies rely on quantitative analyses, focusing primarily on variable relationships rather than examining the actual experiences and decision-making processes of educators (Al-Zahrani and Alasmari, 2024; Chen et al., 2024; Saif et al., 2024; Shoaib et al., 2024).

Meanwhile, AI-supported intelligent educational tools have been increasingly examined, including applications in smart course management, intelligent assessment, automated student inquiries, and academic writing assistance (Hu, 2022). The majority of studies have been conducted in comprehensive or research-intensive universities, while studies specifically examining AI adoption in vocational education institutions remain relatively scarce (Al-Zahrani and Alasmari, 2025). The vocational education system has distinct pedagogical models, technological demands, and instructional approaches that differ significantly from those of traditional universities. However, there has been limited systematic research exploring how these differences influence the adoption of AI technologies in higher vocational education.

The primary research gaps in the current literature can be summarized as follows: first, existing studies predominantly focus on faculty or students in traditional universities, with relatively little attention given to lecturers in HVEIs. Second, research methodologies are largely quantitative, relying on survey-based studies grounded in TAM or UTAUT, whereas few studies adopt qualitative approaches to gain an in-depth understanding of educators' subjective experiences and the contextual factors influencing technology adoption. Third, research on AI adoption in education has largely overlooked the unique characteristics of vocational education, failing to address how AI technologies can be effectively integrated into skill-based teaching practices.

Adopting AI-powered chatbots

Artificial intelligence (AI)-powered chatbots, defined as automated conversational agents that simulate human-like interactions, have become an integral component of digital transformation in higher education (Casheekar et al., 2024). These AI-driven systems leverage natural language processing (NLP) and machine learning (ML) to provide real-time responses, facilitate information retrieval, and assist in administrative and instructional tasks. Over the past decade, AI chatbots have evolved from basic rule-based systems to sophisticated generative AI models capable of understanding complex queries and engaging in adaptive learning interactions. Their adoption in educational settings has expanded significantly, with applications in student engagement, academic advising, automated grading, and intelligent tutoring (Wang and Li, 2024).

The Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) have been extensively utilized to examine the determinants of AI adoption. These models identify key factors—including perceived usefulness, perceived ease of use, social influence, and facilitating conditions—as primary drivers of technology acceptance (Rejali et al., 2023; Rouidi et al., 2022; Zou and Jiang, 2024). While these constructs provide a robust analytical foundation, recent research has underscored the mediating role of attitude in shaping lecturers' adoption decisions. Despite the structured insights offered by TAM and UTAUT, as Table 1 illustrates, their applicability to vocational education remains insufficiently explored. The distinct characteristics of skill-based learning environments necessitate further research on how AI-powered chatbots can be effectively integrated into vocational teaching and assessment practices.

However, existing research has predominantly focused on faculty members in traditional universities, largely neglecting the unique adoption behaviors of instructors in higher vocational education institutions. The teaching methodologies employed in HVEIs differ considerably from those in research-intensive universities, influencing how faculty engage with emerging technologies. First, vocational curricula are heavily practice-oriented, emphasizing hands-on skill acquisition and industry-specific training. Current AI applications in education primarily support knowledge transmission rather than skill-based learning, raising concerns regarding their applicability in vocational education settings (Dahalan et al., 2024). Second, higher vocational education instructors have distinct career trajectories compared to university faculty, as their primary focus is often on short-term educational outcomes and practical training rather than on research-driven technological innovations (Perusso and Wagenaar, 2022). Third, HVEI faculty often experience heightened barriers to technology adoption due to a lack of institutional investment in digital infrastructure and professional development programs, further complicating AI integration in vocational teaching environments (Koljonen and Chan, 2024). Despite these challenges, limited research has systematically examined the structural barriers faced by vocational educators or the specific contexts in which they interact with AI technologies.

Table 1. Review of UTAUT and TAM for adopting AI technologies.

Model	Source	Domain of measure	Variables
UTAUT/TAM	Nikolopoulou et al. (2021)	Teachers' Acceptance of AI Technology	Perceived usefulness, Effort expectancy, Facilitating conditions, Hedonic motivation, Habit, Social Influence
	Jiang et al. (2025)	Teachers' intention to use AI tools for teaching outcomes.	Perceived ease of use, Effort expectancy, Facilitating conditions, Hedonic motivation, Social Influence; Price value; Habit
	Hu et al. (2025)	Teacher's adoption of AI tools	Social influence, Effort expectancy, Facilitating conditions, Hedonic motivation, Price value; Habit
	Chanda et al. (2025)	Teacher's acceptance of AI tools	Facilitating conditions, Hedonic motivation, Social Influence; Habit; Trust; Privacy concerns

RESEARCH METHOD

This study employs a snowball sampling with semi-structured interviews for data collection. Interviews are from December 6 to December 15, 2024. The participants consist of 30 lecturers from 10 vocational colleges in China, as shown in Table 1. Data recovery was through a 1-to-1 interview model, continued 30-60 min. With participants' consent, all interviews were recorded, transcribed verbatim, and reviewed to ensure accuracy.

The collected data were analyzed using grounded theory, following a three-stage coding process: open coding, axial coding, and selective coding (Cheng et al., 2024). In the open coding stage, interview transcripts were systematically analyzed to identify recurring concepts and categorize initial themes. The nature of grounded theory is to develop theories that address a social process grounded in real experience that would be appropriate to understand compliance with lecturers with the use of AI chatbots for academic performance. The axial coding stage involved refining these categories by examining relationships among key concepts and identifying overarching themes, such as perceived ease of use, instructional adaptability, institutional support, and barriers to adoption. Finally, during selective coding, the core categories were synthesized into a conceptual framework that explains the factors influencing AI adoption among vocational college lecturers.

Table 2. Information of the participants.

No.	Age	Title	Gender	Discipline	Institution
S1	35	Lecturer	Male	Computer Science	Beijing Information Technology College
S2	40	Senior Lecturer	Female	Education	Beijing Information Technology College
S3	32	Associate Professor	Male	Engineering	Beijing Information Technology College
S4	29	Lecturer	Female	Linguistics	Guangdong Light Industry Vocational and Technical College
S5	33	Senior Lecturer	Male	Business Management	Guangdong Light Industry Vocational and Technical College
S6	38	Professor	Female	Social Sciences	Guangdong Light Industry Vocational and Technical College
S7	30	Lecturer	Male	Computer Science	Zhejiang Institute of Mechanical and Electrical Engineering
S8	34	Senior Lecturer	Female	Engineering	Zhejiang Institute of Mechanical and Electrical Engineering
S9	28	Associate Professor	Female	Linguistics	Zhejiang Institute of Mechanical and Electrical Engineering
S10	37	Lecturer	Male	Education	*Shanghai* Technical Institute of *Electronics Information*
S11	42	Senior Lecturer	Female	Business Management	*Shanghai* Technical Institute of *Electronics Information*

Table 2. Continues.

S12	31	Associate Professor	Male	Computer Science	*Shanghai* Technical Institute of *Electronics Information*
S13	36	Lecturer	Female	Engineering	Jiangsu Vocational Institute of Commerce
S14	41	Senior Lecturer	Male	Education	Jiangsu Vocational Institute of Commerce
S15	33	Associate Professor	Female	Social Sciences	Jiangsu Vocational Institute of Commerce
S16	29	Lecturer	Male	Computer Science	Sichuan Engineering Technical College
S17	34	Senior Lecturer	Female	Engineering	Sichuan Engineering Technical College
S18	39	Professor	Male	Linguistics	Sichuan Engineering Technical College
S19	32	Lecturer	Female	Business Management	Shandong Business Institute
S20	37	Senior Lecturer	Male	Education	Shandong Business Institute
S21	28	Associate Professor	Female	Computer Science	Shandong Business Institute
S22	33	Lecturer	Male	Engineering	Hunan Industrial Vocational College of Engineering
S23	38	Senior Lecturer	Female	Linguistics	Hunan Industrial Vocational College of Engineering
S24	30	Associate Professor	Male	Social Sciences	Hunan Industrial Vocational College of Engineering
S25	31	Lecturer	Female	Business Management	Wuhan Vocational College of Science and Technology
S26	36	Senior Lecturer	Male	Education	Wuhan Vocational College of Science and Technology
S27	33	Associate Professor	Female	Computer Science	Wuhan Vocational College of Science and Technology
S28	40	Lecturer	Male	Engineering	Chongqing College of Electronic Engineering
S29	35	Senior Lecturer	Female	Linguistics	Chongqing College of Electronic Engineering
S30	34	Associate Professor	Male	Social Sciences	Chongqing College of Electronic Engineering

RESULTS

Open coding

The open coding phase of this study systematically identifies key factors shaping lecturers' adoption of AI-powered chatbots (AIPC) in higher vocational education. Through a comprehensive analysis of interview data, Table 3 shows the ten primary themes, reflecting the institutional, technological, cognitive, behavioral, and pedagogical dimensions of AIPC adoption. These themes provide insights into how organizational support, technological infrastructure, personal competencies, and pedagogical requirements interact to influence lecturers' engagement with AI technologies in academic settings.

The facilitating conditions category highlights the significance of institutional support, training programs, and financial resources in promoting the effective integration of AIPC.

Technological readiness explores the extent to which system compatibility, stability, and functionality affect lecturers' ability to utilize AI tools in teaching (Falebita and Kok, 2024).

Perceived usefulness reflects how AIPC contributes to workflow efficiency, automation, and pedagogical enhancement, shaping lecturers' motivation to incorporate AI-driven solutions.

The social influence category examines the role of peer engagement, student expectations, and administrative encouragement in shaping lecturers' perspectives on AI adoption (Kim, 2024).

Digital literacy considers lecturers' technical competence and confidence in using AIPC, which directly impacts their willingness to integrate AI technologies into instructional practices (Ou et al., 2024).

Beyond factors facilitating adoption, the adoption barriers category encapsulates technical, pedagogical, and institutional constraints that may hinder successful implementation (Mubarik et al., 2024).

Pedagogical fit evaluates AIPC's adaptability to different disciplinary requirements, as certain subject areas may require more tailored AI applications.

Data security reflects concerns regarding student privacy, ethical considerations, and institutional compliance, which influence acceptance and usage patterns.

Finally, teaching interaction enhancement assesses AIPC's ability to support real-time engagement, personalized learning experiences, and interactive classroom dynamics, further shaping lecturers' perceptions of its value.

Table 3 presents a structured summary of these thematic categories, incorporating representative statements from interview participants that illustrate how these factors manifest in practice. These findings establish a foundation for further analysis, where the relationships among these key dimensions will be explored in greater depth.

Table 3. Open coding results.

Theme	Original statements (Descriptive discourse)
Facilitating conditions	"The university provides AI technology training, but it is primarily theoretical, lacking hands-on practical guidance." (S12) "If the university could allocate specific funding for AIPC usage, I would be more inclined to adopt it." (S20) "The current IT support team lacks expertise in AIPC, making it difficult to resolve technical issues promptly." (S5)
Technological readiness	"Some AI tools are incompatible with our teaching system, causing significant issues with data synchronization." (S7) "If the AIPC system were more stable and free from unexpected errors, I would be more willing to use it." (S18) "The intelligent feedback mechanism of AIPC needs improvement, as it currently only provides superficial suggestions." (S9)
Perceived usefulness	"AIPC helps me manage course content, reducing repetitive tasks and allowing me to focus more on students." (S14) "Although AIPC improves grading efficiency, its ability to analyze complex problems remains limited." (S27) "The data analytics provided by AIPC make it easier for me to track students' learning progress." (S11)
Social influence	"My colleagues are experimenting with AIPC, and if it proves effective, I will consider using it as well." (S9) "Some students enjoy AI-based interactions, while others still prefer traditional teaching methods." (S21) "The university administration's attitude toward AI technology promotion directly affects our willingness to use it." (S13)
Digital literacy	"I am not very proficient with AI tools yet and require additional time to learn how to use them effectively." (S25) "If there were AI training programs specifically designed for lecturers, I would feel more confident in adopting it." (S17) "Younger lecturers tend to accept AI more readily, whereas older lecturers face greater challenges in adapting." (S8)
Adoption barriers	"AIPC needs more localized features; its current content is primarily based on generalized teaching scenarios." (S4) "If AI cannot understand specialized terminology, its usefulness will be greatly reduced." (S26) "AIPC relies on an internet connection, but sometimes network conditions are unstable." (S10)
Pedagogical fit	"AIPC is more suitable for humanities courses, but its effectiveness in STEM education is limited." (S19) "In language learning courses, AIPC can simulate dialogues and assist students in practicing communication." (S3) "Currently, AIPC primarily supports theoretical courses, but its functionality for practical courses remains inadequate." (S28)

Table 3. Continues

Data security and privacy	"I am concerned that AIPC may store students' personal data, which poses security risks." (S23) "The current encryption measures for AIPC data are insufficient, raising privacy concerns." (S16) "Some students are reluctant to use AIPC because they do not want their learning data to be recorded." (S30)
Teaching interaction enhancement	"AIPC makes the classroom more engaging, encouraging students to participate actively." (S24) "AI can automatically generate explanations based on students’ questions, improving teaching efficiency." (S2) "Although AI can provide instant feedback, it still cannot fully replace the role of lecturers." (S22)
Attitude mediation	"AI tools have indeed improved my teaching efficiency, but I am still uncertain whether they are suitable for all classroom settings." (S15) "I am cautious about AI-based teaching. Although some colleagues are experimenting with it, I prefer to observe more real-world cases before making a decision." (S9) "If the AI feedback system were more intelligent and could genuinely assist students in learning, I would be more willing to use it." (S27)

Axial coding

Building upon the open coding phase, axial coding consolidates various categories into broader, interconnected themes, revealing the key mechanisms influencing the adoption of AIPC among lecturers in higher vocational education. This study identifies three core themes: technology adoption and institutional support, social and psychological mechanisms, and practical challenges, each representing a critical dimension of the AIPC adoption process.

Technology adoption and institutional support highlight the role of facilitating conditions, technological readiness, and perceived usefulness in shaping lecturers’ willingness to adopt AIPC. Their adoption decisions are influenced by the maturity of the technological platform, the availability of institutional resources, and the perceived value of AIPC in educational settings. For instance, participants noted that system compatibility, stability, and the provision of technical training and financial support directly impact their likelihood of integrating AIPC into their teaching practices.

Social and psychological mechanisms focus on social influence, digital literacy, and the mediating role of attitude in AIPC adoption. Lecturers’ attitudes serve as a critical intermediary, shaped by peer validation, student feedback, and external support systems. Interviews revealed that the adoption behaviors of colleagues and students’ acceptance of AI tools significantly influence lecturers’ decision-making, while higher levels of digital literacy enable smoother adoption and integration of AIPC.

Practical challenges uncover that even when lecturers express a willingness to adopt AIPC, practical feasibility, technological limitations, curriculum adaptability, and data security concerns can influence their final decisions. For example, participants indicated that AIPC lacks sufficient customization for certain disciplines, presents technical reliability issues, and raises concerns regarding data privacy and security. Table 4 presents the results of axial coding, further illustrating how these factors collectively shape the decision-making process for AIPC adoption.

Table 4. Axial coding results.

Axial theme	Associated open coding categories	Representative interview statements
Technology Adoption and Institutional Support	Facilitating conditions, technological readiness, perceived usefulness	"The university provides AI training, but it is too theoretical and lacks hands-on practice, making adoption challenging." (S12) "AIPC improves administrative efficiency but needs better integration with the LMS." (S18) "If the university provides financial support, I would be more willing to adopt AIPC." (S20)
Social and Psychological Mechanisms	Social influence, digital literacy, attitude mediation	"Seeing my colleagues experiment with AI tools makes me more inclined to explore their potential in teaching." (S9) "Some students enjoy AI interactions, but others prefer traditional teaching methods, making it difficult to strike a balance." (S21)

Table 4. Continues.

Practical Challenges	Adoption barriers: Data security and privacy	"I lack proficiency in AI tools, and without structured training, I remain hesitant about adopting AIPC." (S25) "If AI tools continue to improve and better align with my teaching needs, I would be willing to use them in the long term." (S15) "AIPC needs more localized features; currently, its content is too generalized and does not adequately support specialized courses." (S4) "Concerns about data security make me hesitant to use AIPC, especially regarding the storage of student data." (S23)

Selective coding

At the final stage of the coding process, this study consolidates the core category—AIPC integration framework in vocational education, which systematically explains how technological support, social influence, and individual acceptance collectively shape the adoption pathways of AIPC. This framework reflects the multidimensional interaction between institutional structures, technological readiness, psychological factors, and practical constraints, providing a comprehensive theoretical foundation for understanding the key determinants influencing AIPC adoption among lecturers in higher vocational education (HVEIs).

Define the variables

Table 5. Operational definition of variable.

Variable	Definition
Social influence	The effect that the opinions and behaviors of others (such as peers, instructors, and friends) have on the lecturer's behavioral intentions or usage patterns of using AI chatbots for academic performance.
Digital literacy	The ability of lecturers to effectively navigate, evaluate, and utilize AI chatbots for academic performance.
Attitude mediation	A lecturer’s overall evaluation of using AI-supported chatbots for academic performance. It encompasses the lecturer’s feelings, beliefs, and predispositions towards adopting and using AI chatbots.
Facilitating conditions	The presence of necessary resources and support that enable lecturers to utilize AI chatbots for academic performance effectively.
Technological readiness	The technological platform, the availability of institutional resources, and the perceived value of AI chatbots.
Perceived usefulness	The degree to which a lecturer believes that using AI chatbots will enhance their job performance or daily life.
Adoption barriers	The degree of AI chatbots' technical, pedagogical, and institutional constraints that may hinder successful implementation for lecturers.
Pedagogical fit	The degree to evaluate AI chatbots' adaptability to different disciplinary requirements for lectures.
Data security and privacy	The degree to regarding student privacy, ethical considerations, and institutional compliance, which influence acceptance and usage patterns of AI chatbots for lecturers.
Technology Adoption and Institutional Support	AI adoption relies on technological readiness, facilitating conditions, and perceived usefulness. Adequate training, financial support, and stable infrastructure encourage adoption, while system incompatibility, instability, or insufficient hands-on training hinder lecturers’ willingness to integrate AI-powered chatbots (AIPC).

Table 5. Continues.

Social and Psychological Mechanisms	Social influence, digital literacy, and attitude mediation shape adoption decisions. Peer engagement, student expectations, and institutional encouragement positively influence lecturers' perceptions. A high level of digital literacy and a positive attitude facilitate adoption, whereas skepticism or lack of confidence may lead to resistance.
Practical Challenges	Adoption is constrained by technological limitations, pedagogical fit, and data security concerns. Poor adaptability to specific disciplines, system challenges, or student privacy issues may discourage lecturers, even when external support is strong. Without addressing these concerns, full-scale AIPC implementation remains uncertain.

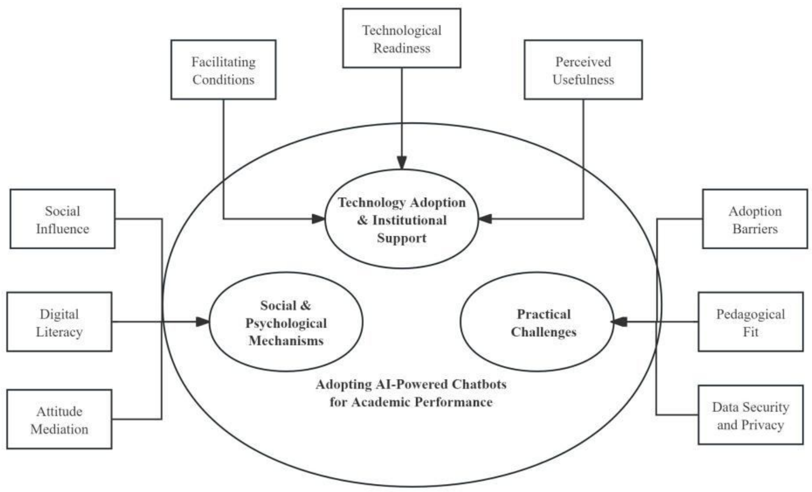

Figure 3. Qualitative model for adopting AI-powered chatbots for academic performance.

Figure 3 presents a qualitative model that illustrates the key determinants influencing the adoption of AI-powered chatbots (AIPC) for academic performance among lecturers in higher vocational education institutions (HVEIs). The model is developed based on the findings from grounded theory analysis, incorporating three primary dimensions: Technology Adoption and Institutional Support, Social and Psychological Mechanisms, and Practical Challenges.

DISCUSSION

By employing a qualitative approach, this study provides an in-depth exploration of AIPC for academic performance. Firstly, this research extends AI adoption research to the vocational education sector. Prior studies on AI in higher education have primarily relied on technology acceptance models such as TAM, using survey-based methods to examine factors influencing faculty and student adoption of AI tools (Sova et al., 2024). However, such models tend to emphasize individual cognitive and behavioral factors while neglecting the structured organizational context in which vocational educators operate. Unlike research universities, where faculty members have greater flexibility in technology use, lecturers in vocational institutions are embedded within institutional frameworks that strongly shape their adoption decisions (Hennessy et al., 2022). This study constructs a theoretical framework specific to vocational education, highlighting the critical role of social influence, digital literacy, attitude mediation, facilitating conditions, technological readiness, perceived usefulness, adoption barriers, pedagogical fit, data security and privacy in AI adoption.

Furthermore, this study introduces the concept of "institutionally driven technology adoption" in vocational education, emphasizing the decisive role of institutional policies, administrative support, and structured training programs in shaping lecturers' willingness to integrate AI-powered chatbots into their teaching. Unlike previous studies that largely focus on individual attitudes and competencies in technology adoption (Antonietti et al., 2022), this study demonstrates that vocational educators are highly dependent on institutional directives, financial resources, and access to professional development programs. The findings suggest that AI adoption in vocational education is not merely an individual choice but is deeply embedded in institutional structures, where top-down initiatives and administrative leadership significantly influence lecturers' decision-making processes. This institutional dependency differentiates vocational education from other higher education contexts and provides new theoretical insights into how organizational support mechanisms facilitate or hinder AI integration.

This study also identifies pedagogical adaptability as a key determinant of AI adoption in vocational education, thus expanding existing technology adoption research beyond the traditional constructs of perceived usefulness and ease of use (Zhang et al., 2022). The findings reveal significant disciplinary disparities in AI adoption, with humanities and business lecturers more likely to embrace AI-powered chatbots for classroom interaction and content management, while engineering and technical lecturers express reservations about the technology's limited capacity to support practical training. This differentiation suggests that AI adoption in vocational education is not solely contingent on its functional benefits but is also critically dependent on its alignment with course-specific pedagogical requirements (Karrenbauer et al., 2023).

In addition to institutional and pedagogical factors, this study extends the theoretical discourse on social influence in technology adoption. Existing research on AI adoption typically frames social influence in terms of peer recommendations, student expectations, and general external pressures (Spandagos et al., 2021). However, this study reveals that in vocational education, social influence operates on multiple levels, encompassing not only peer usage but also administrative encouragement, institutional culture, and industry expectations. The findings demonstrate that when institutional leaders actively promote AI adoption and establish clear implementation guidelines, lecturers exhibit a significantly higher willingness to integrate AI-powered chatbots into their teaching. Conversely, the absence of formal institutional support results in uncertainty and reluctance toward AI adoption. Additionally, vocational lecturers, whose teaching objectives are closely aligned with industry requirements, are also influenced by external stakeholders such as corporate partners and industry mentors.

To effectively integrate AI-powered chatbots (AIPC) into vocational education, a multi-stakeholder approach is essential. Policymakers should enhance funding mechanisms and regulatory frameworks to ensure vocational institutions have adequate financial and technical resources for AI adoption. As the study highlights, institutional support is a decisive factor influencing lecturers' willingness to adopt AI chatbots. Therefore, educational authorities should incentivize AI-driven innovations through targeted subsidies, professional development programs, and infrastructure investments that address the technological disparities between research universities and vocational institutions. Moreover, policies must be tailored to accommodate the unique pedagogical needs of vocational training, ensuring that AI applications extend beyond knowledge transmission to support skill-based, experiential learning. This requires aligning AI adoption policies with national workforce development strategies and fostering collaboration between academia and industry to create AI-driven tools that are adaptable to real-world vocational training contexts.

At the institutional level, administrators must implement structured AI capacity-building programs to address the digital literacy gap among vocational lecturers. As the findings suggest, many educators hesitate to adopt AI due to limited digital competencies and a lack of specialized AI training. Institutions should develop comprehensive training programs that focus on both technical proficiency and pedagogical integration, ensuring that AI-powered chatbots are leveraged effectively in diverse teaching environments. Additionally, AI developers must prioritize user-centric design, refining chatbots to enhance pedagogical fit, improve data security, and ensure accessibility across different instructional domains. Given lecturers' concerns regarding data privacy and security, institutions must work closely with technology providers to establish clear data governance frameworks, ensuring compliance with ethical standards and institutional policies. By fostering a collaborative ecosystem between government agencies, vocational institutions, and AI developers, the systematic adoption of AI-powered chatbots can lead to improved teaching quality, better alignment with industry needs, and a transformative shift toward digitalization in vocational education.

Conclusion

This study provides a conceptual framework to understand the adoption of AI-powered chatbots among lecturers in higher vocational education institutions (HVEIs). The findings reveal that AI adoption in vocational education is not merely an individual cognitive and behavioral decision but a systemic process shaped by institutional support, pedagogical adaptability, and social influence. Unlike faculty in research-intensive universities, lecturers in vocational institutions exhibit a higher dependency on institutional policies, technological support, and industry-driven demands, making AI adoption a more structured and externally mediated process rather than one based solely on personal perceptions of usability and usefulness. Thus, the study underscores the necessity of aligning AI implementation with the institutional structures, curricular needs, and management systems of vocational education to ensure its effectiveness in supporting teaching and learning.

While this study provides important insights into AI adoption in vocational education, several limitations remain, which open avenues for future research. First, although the study captures diverse perspectives through qualitative analysis, its findings are based on data collected from China. Given that vocational education systems and AI adoption policies vary across countries, future research could explore cross-cultural comparisons to examine how different regulatory frameworks, industry linkages, and digital infrastructures influence AI adoption in vocational education. Second, this study focuses on lecturers' perspectives; however, the role of students in AI adoption remains underexplored. Future studies could investigate how AI-powered chatbots impact student engagement, learning outcomes, and digital literacy in vocational education. Third, as AI technologies continue to evolve, their potential applications in vocational training—particularly in AI-assisted practical simulations, hands-on training, and industry certification processes—remain an emerging area for research. Future studies should explore the long-term effects of AI adoption on teaching quality, vocational skill development, and workforce readiness, offering empirical evidence of AI's transformative impact on vocational education.

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