

From Classroom to Career: Understanding AI Dependency and AI Literacy of Hong Kong University Students

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Abstract

This study examines perceptions of artificial intelligence (AI) in the workplace, students' dependence on AI, and how such dependence mediates the usefulness of AI in their academic studies and perceived work skills in future workplaces, as well as the moderating role of AI literacy. Indeed, global higher education and future workplaces are undergoing significant technological disruption, especially regarding AI, which has a widespread impact across industry sectors. This study fills an essential gap in existing literature by exploring AI literacy. Grounded in the Technology Acceptance Model (TAM) and Self-Efficacy Theory, this study adopts a cross-sectional design and collects data from a sample of 353 Hong Kong undergraduate students through online surveys. Results reveal positive relationships among perceptions of AI, dependence on AI, AI usefulness, and future work skills. Moreover, AI literacy significantly moderates these relationships. These findings highlight AI literacy as an essential factor and underscore its importance in curriculum design and employability.

Keywords: AI literacy, AI dependence, AI usefulness, Future work skills, Higher education

1. Introduction

The AI era is akin to a new form of electricity, becoming the central driver of change in higher education and across different industry sectors. According to Feuerriegel et al. (2024), generative AI is gaining prominence for generating new materials such as words and images, and, in turn, reshaping future student learning, career preparation, and workplaces. It is reshaping the expectations of graduating students regarding these AI skills, preparing them for future workplaces. Due to this transformation, many higher education institutions have launched AI courses as a compulsory requirement for graduates. It is believed

that AI integration can benefit students in their academic studies and future employability. Therefore, this research aims to examine how students perceive and interact with AI in educational and workplace contexts, and to consider whether students' AI literacy is an essential competency for the future workforce.

In an AI-driven future, this research proposes a mediated-moderated model for AI literacy research, as it remains in its infancy. Grounded in the Technology Acceptance Model (TAM) and Self-Efficacy Theory, this study aims to address these gaps by investigating how perceptions of AI in the workplace relate to dependence on AI and how this dependence influences two outcomes: the usefulness of AI in study and work skills in the future workplace. This study will further explore whether AI literacy moderates these relationships.

Therefore, this study addresses two overarching research questions:

1. How does dependence on AI mediate the relationship between perceptions of AI in the workplace and the usefulness of AI in study and the development of future work skills?
2. To what extent does AI literacy moderate the effects of AI dependence on the usefulness of AI in study and work skills in the future workplace?

While the Technology Acceptance Model (TAM) utilises both perceived usefulness and perceived ease of use to predict user behaviour regarding initial technology adoption, this study focuses on assessing functional utility, as universities have already provided various AI subscription services to students who widely use them. By situating the research in the Hong Kong context, this study advances the literature on higher education, AI readiness, and future workforce preparation.

2. Methodology

A quantitative survey method was employed, and participants were recruited using a convenience sampling approach via mass email invitations. A total of 353 valid responses were collected from students at a higher education institution in Hong Kong between 2024 and 2025. Participation was voluntary and anonymous. The overall response rate was approximately 2.26% based on the total number of students contacted. The institution has integrated AI coursework across all academic programmes so as to ensure all respondents have baseline exposure to AI literacy and application. This was done to enhance the relevancy and internal consistency of the sample.

All measures were drawn from previous research literature. Respondents were asked to rate items on a 7-point Likert scale (1 = strongly disagree to 7 = strongly agree).

- **Perception of AI in the workplace** (8 items), **usefulness of AI in study** (7 items), and **work skills in the future workplace** (7 items) were adapted from Rožman et al. (2023). Sample items for perception of AI in the workplace include: *“AI makes faster business decisions based on outputs from cognitive technologies.”*
- Sample items for usefulness of AI in study include: *“I think that using AI would save me a lot of time in studying.”*
- Sample items for work skills in the future workplace include: *“Analytical thinking and innovation are important skills to have in the workforce,”* and *“Active learning and learning strategies are important skills to have in the workforce.”*

Dependence on AI was drawn from Morales-García et al.’s (2024) 5-item scale. Sample items include: *“I constantly need validation or feedback from AI systems to feel confident in my decisions.”*

Finally, the **AILQ scale** (32 items) was adapted from Ng et al. (2024). The Ng et al. (2024) AILQ scale is designed to assess students’ AI literacy development through the affective, behavioural, cognitive, and ethical (ABCE) framework.

- The **affective dimension** measures intrinsic motivation and self-efficacy. Sample items include: *“Learning AI is interesting,”* and *“I believe I can master AI knowledge and skills.”*
- The **behavioural dimension** evaluates commitment and collaboration. Sample items include: *“I will continue to use AI in the future,”* and *“I try to work with my classmates to complete AI learning tasks and projects.”*
- The **cognitive dimension** gauges lower- to higher-order skills. Sample items include: *“I know what AI is and recall the definitions of AI,”* and *“I can evaluate AI applications and concepts for different situations.”*
- The **ethical dimension** examines students’ critical understanding of responsible AI use. Sample items include: *“I understand how misuse of AI could result in substantial risk to humans,”* and *“I think that people should be accountable for using AI systems.”*

Data Analysis

Data were analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM) because this method is more appropriate than others for analysing an overall model with multiple latent variables and indicators simultaneously, where normal distribution is not required (Hair et al., 2017).

Measurement and Structural Models

We followed the guidelines suggested by Hair et al. (2017) to assess the measurement model. First, factor loadings, composite reliability (CR), and Cronbach's alphas were used to evaluate internal consistency. Table 1 shows that all items demonstrated satisfactory loadings, which were all above the recommended threshold of 0.70. Moreover, all constructs met the 0.70 criteria for CR and Cronbach's alpha, reflecting acceptable internal consistency.

Table 1 also indicates satisfactory results for convergent validity, as indicated by average variance extracted (AVE) values. All constructs exceeded the 0.50 benchmark for AVE values, thus indicating adequacy of item convergence within each construct. To assess discriminant validity, suggested by Henseler et al. (2015), we used the heterotrait-monotrait (HTMT) ratio of correlations. All constructs showed sufficient discriminant validity as all HTMT values were below the threshold of 0.90 (see Table 2).

After confirming the measurement model, we tested the structural model using PLS-SEM with 5,000 bootstrap resamples (Figure 1).

3. Results and Discussion

Overview of Hypotheses

Table 3 shows all path coefficients and significance levels, and Figure 1 visualises the results with all hypotheses. Indeed, perception of AI in the workplace was positively related to dependence on AI ($\beta = 0.450$, $p < 0.001$), supporting H1. Moreover, dependence on AI was positively related to the usefulness of AI in study ($\beta = 0.494$, $p < 0.001$) and work skills in the future workplace ($\beta = 0.242$, $p < 0.001$), supporting H2a and H2b. Regarding the indirect relationships, results also show that there were indirect relationships between perception of AI in the workplace and usefulness of AI in study ($\beta = 0.223$, $p < 0.001$) and work skills in the future workplace ($\beta = 0.109$, $p < 0.001$) via dependence on AI, offering support to H3a and H3b.

Finally, regarding the moderating effects of AI literacy, results show that AI literacy moderated the direct relationships between dependence on AI and usefulness of AI in study ($\beta = -0.098$, $p < 0.01$), and between dependence on AI and work skills in the future workplace ($\beta = -0.12$, $p < 0.01$), such that when AI literacy was high, the positive direct relationships were dampened, thereby offering support to H4a and H4b. Finally, for the mediated moderating effects of H5a and H5b, Table 4 shows that results also offer support for the mediated moderating relationships at different levels; specifically, AI literacy moderated

the indirect relationships between perception of AI in the workplace and usefulness of AI in study via dependence on AI, and between perception of AI in the workplace and work skills in the future workplace via dependence on AI.

Perception of AI in the Workplace, Dependence on AI, and Usefulness of AI in Study

Students who perceived AI as beneficial in workplace settings usually display stronger dependence on AI for personal and academic tasks (Rožman et al., 2023). These findings align with the TAM, which posits that repeated interactions with and task completion using AI will enhance perceived usefulness of AI in study and future work skills. Moreover, Self-Efficacy Theory can explain the reciprocal process of using AI that leads to positive outcomes, which can enhance the perceived usefulness of AI and self-efficacy.

Bandura's (1997) self-efficacy theory posits that one's self-efficacy is developed through mastery experience, vicarious experience, verbal persuasion, and physiological states. When individuals have confidence in their ability to attain a task, they are more likely to engage with it, persist through difficulties, and achieve better outcomes. For instance, students accumulate mastery experience using AI tools for academic tasks. These interactions boost their confidence in their technological capabilities. Vicarious experiences, such as observing peers using AI in other areas, such as integrating AI to assist their study routine, and receiving encouragement from the institution, further reinforce their self-efficacy. If students achieve a successful outcome, such as improved efficiency in completing the task with less effort while producing a consistent level of output, or resulting in better grades, this increases their self-efficacy, and in turn promotes further and more frequent usage of AI. They perceive it as a useful tool for achieving their goals. Eventually, this creates a positive reciprocal and self-reinforcing cycle. Indeed, successful AI use enhances self-efficacy; stronger self-efficacy promotes deeper engagement with AI; and repeated positive outcomes amplify perceived usefulness.

However, to support healthy reliance rather than overdependence on AI, higher education institutions should build students' self-efficacy in handling core academic work before AI use.

Dependence on AI, Usefulness of AI in Study, and Work Skills in the Future Workplace

Apart from the positive relationship between dependence on AI and the usefulness of AI in study, dependence on AI also predicted confidence in future work skills. Using AI, students tend to improve their data-handling, communi-

cation, and problem-solving skills, which are valuable in contemporary workplaces and better prepare them for future employment. Indeed, Santos-Jaén et al. (2025) state that exposure to AI increases perceived competence even when actual skill development may vary.

Moderating Role of AI Literacy

Our study further explores the moderating role of AI literacy, and it moderates the relationship between dependence on AI and both outcomes, namely academic and career-related outcomes. Drawing on Bandura's (1997) self-efficacy theory to explain an interesting finding—that is, high AI literacy reduced the strength of these relationships—a certain level of AI literacy does not simply increase the positive efficacy cycle but promotes balanced engagement, prevents over-reliance, and supports professional autonomy and competency.

As defined by its four aspects (to know and understand, to use and apply, to evaluate and create, and ethical use), students with high AI literacy possess stronger skills in evaluating the results created for them, leading to a clearer understanding of their capabilities and limitations. For example, they may use AI tools to generate points for an assignment, but then critically review, modify, refine, and connect the ideas using their own judgment. Therefore, even though they use AI often, their perceived usefulness stems from a rational evaluation of practical benefits rather than emotional dependence or insecurity.

In contrast, students with lower literacy doubt their own abilities and view AI as a useful tool to fill their skills gap. They may constantly seek validation from AI, ask the system to generate the whole answer for them to adopt, or feel anxious about not using it to complete academic tasks. Eventually, they rely on it for support, which reinforces perceived usefulness. These findings help to explain that AI literacy serves as a protective factor.

4. Implications

Despite the benefits of AI, increasing excessive dependence on AI requires careful institutional attention and proactive monitoring in global education and across industry sectors. Productive use occurs when AI supports learning by providing analysis or suggestions, while students still critique the result using their own judgment and make the final decisions. In this case, AI strengthens their abilities and professional skills rather than replacing them. The boundary into harmful dependence is crossed when its application transitions from augmentation to substitution, resulting in decreased self-confidence. In this situation, AI is no longer a tool to support learning and leads to weakened independent thinking skills and reduced personal autonomy.

Given the inevitable trend, global universities are advised to continue to establish guidelines for students to strengthen the ethical usage of AI and embed such training into their learning modules. A mandatory disclosure is required for all coursework to state whether they have used such tools. The key is to promote students' self-efficacy while preventing over-reliance. A formative assessment, such as a written critique towards an AI-generated essay, is a balanced way for students to evaluate the weaknesses of AI while applying the knowledge they have learnt throughout the course. Providing their own justification points for each idea can strengthen students' critical thinking and their behavioural competency.

Nonetheless, the targeted approach should view AI as a complement, rather than a substitute for human abilities (Morales-García et al., 2024). In an AI-dominated environment, universities must help to enhance students' AI skills, as well as emotional and psychological competencies; these work skills are needed in the future workplace.

Acknowledgements

N/A

Ethical Declaration Statement

The project has been approved by the CPCE Research Committee of the College of Professional and Continuing Education, The Hong Kong Polytechnic University (Reference Number: RC_ETH_H_439).

Generative AI Policy

The author(s) used Grammarly during the preparation of this work for grammar checking. After utilising the tool/service, the author(s) thoroughly reviewed and edited the content as necessary and assumed full responsibility for the publication's content.

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Appendices

Table 1: Results of the measurement model

Scale and items	Cronbach's Alpha	Composite reliability	AVE
Perception of AI in workplace (PAIW)	0.985	0.986	0.908
Dependence on AI (DAI)	0.942	0.944	0.812
Usefulness of AI in Study (UAIS)	0.952	0.953	0.776
Work Skills in Future Workplace (WFW)	0.982	0.982	0.903
AI Literacy (AIL)	0.993	0.993	0.819

Table 2: HTMT of the constructs

Constructs	AI Literacy	Dependence on AI	Perception of AI in Workplace	Usefulness of AI in Study
AI Literacy				
Dependence on AI	0.488			
Perception of AI in Workplace	0.827	0.465		
Usefulness of AI in Study	0.674	0.698	0.656	
Work Skills in Future Workplace	0.697	0.491	0.690	0.689

Note: Diagonal values represent correlations within constructs; off-diagonal values represent HTMT ratios between constructs.

Table 3: Results summary of the hypotheses

Path	Hypothesis	Path coefficients	t-statistics	p-values	Conclusion
PAIW → DAI	H1	0.450	9.340	0.000	Support
DAI → UAIS	H2a	0.494	9.953	0.000	Support
DAI → WFW	H2b	0.242	4.418	0.000	Support
PAIW → DAI → UAIS	H3a	0.223	6.248	0.000	Support
PAIW → DAI → WFW	H3b	0.109	3.769	0.000	Support
DAIxAIL → UAIS	H4a	-0.098	2.788	0.005	Support
DAIxAIL → WFW	H4b	-0.120	3.107	0.002	Support

Note: PAIW = Perception of AI in workplace; DAI = Dependence on AI; UAIS = Usefulness of AI in study; WFW = Work Skills in Future Workplace; AIL = AI Literacy.

Table 4: Results of the mediated moderating model

PAIW → DAI → UAIS			
Levels of moderator	Coefficient	t-statistics	p-value
High AI Literacy	0.178	4.998	0.000
Low AI Literacy	0.267	6.359	0.000
PAIW → DAI → WFW			
High AI Literacy	0.055	2.403	0.016
Low AI Literacy	0.163	3.889	0.000

Figure 1: Results of the model and hypothesis

