Evaluation of a Professional Development Course on Artificial Intelligence Literacy for Administrative Staff in Hong Kong

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Abstract: *This study examines the implementation and outcomes of an artificial intelligence (AI) literacy course for administrative staff. One hundred and twelve administrative staff from schools, small to medium-sized enterprises, and universities in Hong Kong participated in a 30-hour course, which included the introduction to machine learning concepts, AI tools, and AI ethics. The learning outcomes culminated in a group presentation showcasing the participants' learning achievements. Using the attention, relevance, confidence, and satisfaction model, the motivation survey revealed high participant engagement, with strong correlations between motivation factors. The participants demonstrated positive acceptance of AI tools. Thematic analysis of pre- and post-course reflections highlighted significant improvements in their understanding and application of AI tools, particularly in terms of efficiency and work quality. This study contributes to the underexplored area of AI literacy development among administrative professionals, highlighting the need for tailored workplace training initiatives in future study.*
Keywords: administrative staff, artificial intelligence literacy, motivation survey, professional development, thematic analysis

1. Introduction

The AI Index Report 2024 revealed that 52% of Americans express more concern than excitement about artificial intelligence (AI), an increase from 38% in 2022 (Stanford University, 2024), worrying primarily about AI's impact on their jobs. According to McKinsey & Co. (2023), AI is currently used in 55% of organisations in at least one business unit or function, up from 50% in 2022 and 20% in 2017. Manyika et al. (2017) indicated that administrative roles are among the most vulnerable to AI-driven job elimination. Furthermore, McKinsey & Co.'s May 2024 report projected continued declines in demand for workers in food services, production, customer services, sales, and office support, sectors that already experienced a downturn from 2012 to 2022, through 2030. Thus, although AI is poised to reshape the labour market, it is also expected to enhance productivity and bridge the gap between low- and high-skilled workers (Stanford University, 2024).

Most AI literacy initiatives primarily target K–12 and higher education, focusing on teaching skills (Ahmad et al., 2022; Casal-Otero et al., 2023; Kong et al., 2023). However, there remains a gap in AI literacy education tailored to administrative staff. This study fills this gap by equipping administrators with essential AI knowledge, fostering deeper and more reliable thinking about their career development, and preparing them for an uncertain future. The course is designed to help them (1) use AI to work more efficiently; (2) stay updated on emerging AI tools; (3) evaluate AI tools for their work; and (4) develop motivation to adopt AI tools in the future.

The study answered the following research questions: (1) What factors motivate administrative staff to participate in an AI literacy course? (2) How do administrative staff's perceptions of AI in the workplace evolve throughout the course?

2. Literature Review

2.1. AI Literacy at Work

AI literacy refers to the competencies needed by workers to use AI and establish a synergistic relationship with it (Kong et al., 2021). Despite various definitions, Laupichler et al. (2023) provided a concise definition, emphasising understanding, using, monitoring, and critically thinking about AI applications, independent of the ability to develop AI models.

As the AI literacy framework remains undefined, we adopted the model of Kong et al. (2021) and its three key components: understanding AI concepts, evaluating AI applications, and applying AI concepts to real-world problem-solving. These components align with the four dimensions of AI literacy: (1) cognitive (understanding of AI concepts); (2) metacognitive (use of AI concepts for problem-solving); (3) affective (psychological readiness to use AI); and (4) social (ethics of problem-solving with AI) (Kong et al., 2024).

2.2. The Attention, Relevance, Confidence, Satisfaction Model

The attention, relevance, confidence, satisfaction (ARCS) model is a motivational design framework used for decades in various countries and educational settings. It is a fundamental model of instructional design (Keller, 1987; Li & Keller, 2018). The ARCS model has applications beyond traditional educational environments, including workforce training and professional development. It has been employed to assess motivation and engagement in diverse learning contexts, as demonstrated in studies such as Chang et al. (2019). By focusing on fostering attention, demonstrating relevance, building confidence, and ensuring satisfaction, the ARCS framework offers a robust approach to designing and evaluating instructional interventions.

2.3. Project-Based Learning

Project-based learning (PBL) is an instructional approach that engages learners by immersing them in tasks that involve problem-solving, inquiry, and collaboration. Through PBL, learners are encouraged to seek solutions, ask critical questions, debate ideas, design actionable plans, and effectively communicate with others (Choi et al., 2019). A growing body of research highlights the benefits of PBL in enhancing learners' motivation, problem-solving abilities, teamwork, and communication skills (Zhang & Ma, 2023). For professional training contexts, especially those with limited course durations and diverse participant backgrounds, PBL offers a practical and impactful learning strategy. By simulating real-world challenges, PBL effectively mirrors the complexities of professional environments, equipping learners with the practical skills and decision-making capabilities that traditional teaching methods may not adequately address.

3. Methodology

3.1. Research Design

The course consisted of five lessons, each lasting six hours. The course included three face-to-face teaching sessions, one self-study day (with materials provided), and one project-work day where participants prepared a presentation on their AI product (Table 1).

3.2. Participants

Administrative staff were recruited from K–12 schools, small to medium-sized enterprises (SMEs), and universities in Hong Kong using convenience sampling. We emailed administrative staff of all Hong Kong schools and used available channels to contact SMEs and our university for participant recruitment. Interested individuals submitted an online application alongside self-declaration and consent forms to enrol in the course. No programming experience was required.

A total of 112 administrative staff participated, including 41 men (37%) and 71 women (63%). The age distribution included 24 participants aged 20–30 (21%), 36 aged 31–40 (32%), 34 aged 41–50 (30%), 16 aged 51–60 (14%), and two aged over 60 (2%). Regarding educational attainment, 18 held a diploma or certificate (16%), 67 a bachelor's degree (60%), 26 a master's degree (23%), and one a doctoral degree (1%). In terms of background, 49 participants came from K–12 schools (44%), 37 from SMEs (33%), and 26 from universities (23%).

Table 1. Course content and data sources

Time	Teaching Mode	Topics	Surveys
Week 1	Face-to-face teaching	(1) Concepts of Generative AI (GenAI), data security and ethics (2) Techniques: prompt engineering, material generation (speech-to-text transcription & PowerPoint generation), chatbot creation	Written reflection (pre-course)
Week 2	Self-study	(1) Prompt engineering (2) AI regulatory policies	N/A
Week 3	Face-to-face teaching	(1) Concepts of machine learning and deep learning (2) Techniques: machine learning model building, material generation (MS Word, Excel, Copilot, Images), chatbot creation	N/A
Week 4	Project preparation	Creation of AI artefacts	N/A
Week 5	Face-to-face teaching	Learning about AI using robots	(1) Written reflection (post-course)
	Presentation	Project presentation and peer assessment	(2) Motivation survey (3) Acceptance survey (4) Course evaluation

3.3. Data Collection and Analysis

A mixed-methods approach combining qualitative and quantitative data collection and analysis was used. Pre-course, the participants wrote reflections (50–100 words) on their attitudes towards the AI course and their expectations. Post-course, they reflected on whether their expectations were met (50 –100 words).

We adapted a motivational survey based on the ARCS model, consisting of 12 items rated on a 5-point Likert scale from 1 (strongly disagree) to 5 (strongly agree) to assess the participants' views after the course. Additionally, an AI tools acceptance survey with 18 items rated on a 5-point Likert scale was designed, incorporating six constructs: perceived usefulness, perceived ease of use, attitude towards usage, behavioural intention, self-efficacy, and subjective norm (Chow et al., 2012; Compeau & Higgins, 1995; Davis, 1989; Rafique et al., 2020; Watson & Rockinson-Szapkiw, 2021). Finally, a nine-item course evaluation survey was administered, including six items rated on a 5-point Likert scale and three open-ended questions, to obtain detailed participant feedback on the most beneficial content and areas for improvement.

To address the first research question, descriptive data from the motivation survey were analysed. Qualitative and quantitative data were used to answer the second research question. Descriptive data from the acceptance survey were examined to determine course satisfaction, while a thematic analysis of pre- and post-course reflective writings was conducted to understand participant expectations and learning outcomes. The researchers categorised each participant's reflections based on whether their expectations were met as follows: (1) failed (0 marks): not satisfied and perceived the course as unhelpful; (2) partially satisfied (0.5 marks); (3) satisfied (0.75 marks): happy with unexpected gains despite not meeting initial expectations; (4) fully satisfied (1 mark): fully met expectations and gained additional knowledge.

4. Results

4.1. Motivation

The PBL for Motivation Survey had high reliability (Cronbach's alpha = 0.967) (Table 2). The Attention component had the highest mean of 4.33 (SD = 0.76), indicating that most responses were positive, with some variability. Satisfaction followed closely, with a mean of 4.32 (SD = 0.78), suggesting that the participants were generally satisfied with the course. Relevance had a mean of 4.05 (SD = 0.83), indicating that the participants found the course relevant to their professional development. Confidence received the lowest mean of 3.99 (SD = 0.82), indicating room for improvement in building confidence in using AI at work. Overall, the data reflect a positive perception of all course aspects among the participants.

Table 2. Descriptive statistics for motivation survey variables.

Item	Min	Max	M	SD
Attention	1	5	4.33	0.76
Relevance	1	5	4.05	0.83
Confidence	1	5	3.99	0.82
Satisfaction	1	5	4.32	0.78

4.2. Acceptance

The GenAI Tools Acceptance Survey also had high reliability (Cronbach's alpha = 0.960), with reliability above 0.850 for all six variables. Overall, the survey indicated strong acceptance and positive attitudes towards GenAI tools. Behavioural intention had the highest mean (M = 4.15, SD = 0.83), suggesting that the participants were likely to adopt and continue using GenAI tools in their activities. Perceived usefulness followed closely (M = 4.13, SD = 0.76), indicating that the participants felt that these tools effectively supported their tasks. They showed positive attitudes towards using GenAI tools at work (M = 4.04, SD = 0.76). The mean of self-efficacy was 3.88 (SD = 0.85), indicating that the participants generally felt confident in their ability to use GenAI tools. The mean of subjective norm was 3.76 (SD = 0.90), reflecting the participants' perceptions of social pressure or expectations from peers and authorities regarding the use of GenAI tools. Perceived ease of use received the lowest score (M = 3.40, SD = 0.84), highlighting that although the participants recognised the usefulness of GenAI tools, they found them difficult to use, indicating a need for further professional development.

4.3. Reflection

A qualitative thematic analysis was performed on the reflective writings of the participants, examining their pre- and post-course insights. Initially, 10 codes grouped under four themes were identified after reviewing all reflective writings. Post-course, two new themes and one new code (in *italics* in Table 3) emerged, expanding the classification to 6 themes and 13 codes.

The course had a substantial impact on the participants' perceptions and intentions to use AI tools. Initially, 53.92% of the participants wanted to enhance their work and personal lives by focusing on efficiency (31.34%), quality (12.90%), and creativity (5.53%), expecting AI tools to automate tasks, optimise workflows, and reduce skills barriers (e.g., 'I hope to improve my work efficiency by using at least the simplest AI tools to minimise repetitive and labour-intensive tasks to save time for more important and strategic tasks'). Post-course reflections showed a decline, with only 27.82% of the participants viewing AI as beneficial for work or life, while mentions of efficiency dropped to 16.54%, highlighting application challenges (e.g., 'AI tools are useful for productivity, but practical implementation is complicated'). Mentions of quality and creativity also declined, with the participants recognising the need for a nuanced understanding of AI's capabilities and limitations.

Table 3. Comparison of pre- and post-course reflective writings.

Theme	Code	Pre-Course		Post-Course	
		Frequency	Percentage	Frequency	Percentage
1. Better Work or Life	Total	117	53.92%	74	27.82%
	Efficiency	68	31.34%	44	16.54%
	Quality	28	12.90%	14	5.26%

		Creativity	12	5.53%	12	4.51%
		Management	5	2.30%	2	0.75%
		Information Source	4	1.84%	2	0.75%
2.	Self-development	Total	77	35.48%	99	37.22%
		Skills	27	12.44%	23	8.65%
		Understanding	26	11.98%	51	19.17%
		Competency	24	11.06%	11	4.14%
		Confidence & Planning			14	5.26%
3.	Sharing with Others		7	3.23%	25	9.40%
4.	Thoughts about AI		16	7.37%	21	7.89%
5.	*Course Suggestions*				9	3.38%
6.	*Challenges & Considerations*				38	14.29%
Total			217	100%	266	100%

Note. The frequencies reflect the number of codes, as the participants could refer to multiple aspects in their responses, leading to overlapping frequencies and percentages across different codes and themes.

Mentions of self-development rose from 35.48% to 37.22%, and understanding of AI concepts increased from 11.98% to 19.17%, indicating a deeper conceptual grasp (e.g., 'Learning about GenAI tools was enlightening, enhancing my understanding of AI's potential'). However, mentions of acquiring new skills decreased slightly to 8.65%, suggesting that the participants valued theoretical knowledge over immediate skill acquisition.

Confidence and planning to use and learn about AI tools were mentioned in 5.26% of the post-course reflections. Several participants wanted to stay up to date with AI trends (e.g., 'Taking an AI course was enlightening... It opened my eyes to the ethical implications and societal impact of AI technologies'). This evolution indicates that although the course provided fundamental knowledge, ongoing support is essential to translate learning into practical applications.

Interest in sharing AI knowledge with others increased, from 3.23% pre-course to 9.40% post-course. The participants wanted to educate their colleagues and family members (e.g., 'I'm thrilled to teach others about AI's transformative potential'). Thoughts about AI also increased slightly, from 7.37% to 7.89%, highlighting ongoing discussions about AI's role and ethical implications in broader contexts.

The participants faced challenges in applying AI tools, with 14.29% expressing concerns post-course, such as unsatisfactory results, complex implementation processes, and ethical considerations. One participant highlighted a major issue: 'Senior management scepticism limits access to AI platforms, hindering practical use'. This underscores the importance of promoting AI literacy at all organisational levels.

Participant feedback on course improvement suggested adjustments to the schedule and a reduction in theoretical content. Some requested advanced modules to deepen their understanding, while others hoped for executive participation to facilitate organisational adoption of AI tools. As one participant suggested, 'Promoting AI literacy should start at the executive level'.

Overall, the course effectively enhanced the participants' understanding of AI, as evidenced by their increased focus on understanding rather than immediate practical application. However, the decline in perceived work improvement highlights the need for continued support to translate AI knowledge into practice. Addressing these challenges in future iterations of the course will enhance its impact, enabling administrative staff to better navigate the complexities of AI at work.

To evaluate changes in the participants' reflections, a scoring system was used (2 = significant improvement, 1 = some improvement, 0 = no improvement). The statistical average of these scores was 0.86. The score distribution showed that 4% of the participants (4 responses) demonstrated no improvement, 18% (20 responses) showed some improvement, and 74% (83 responses) exhibited significant improvement.

These results underscore the effectiveness of the AI literacy course in enhancing participants' understanding of AI and its potential applications. However, they also highlight the need for additional support and resources to facilitate the practical implementation of AI tools at work. Addressing these challenges in future courses could enhance the impact of AI literacy training for administrative staff.

4.4. Evaluation

The evaluation survey had high reliability (Cronbach's alpha = 0.916). Items 1–6 aimed to provide a macroscopic view of the participants' experiences. Their descriptive statistics are presented in Table 4. Items 7–9 used open-ended questions to further explore the participants' perspectives on the most and least useful content, as well as suggestions for improvement.

The most useful content was categorised into three main areas: (1) Underlying Concepts, such as machine learning and neural networks, with 23% of the participants finding that this content provided a clearer understanding of fundamental AI concepts; (2) Impact and Evolution, which included ethics, trends, and future directions of AI and their professional development, with 16% of the participants mentioning that this content broadened their horizons in the field; and (3) Tool Use, which encompassed introductions of new tools, available resources, and hands-on practice sessions.

The participants also identified several areas for improvement, such as some content perceived as too difficult (33%), a tight schedule during the teaching process (29%), and challenges in applying AI knowledge to real-world situations (4%). Many participants wanted more support, such as a platform for continued learning and communication or advanced courses offering deeper knowledge and up-to-date information. These suggestions aligned with those mentioned in previous reflections before the course.

Table 4. Descriptive analysis of items.

Item	M	SD
1. I understand GenAI better after attending the course.	4.48	0.60
2. The hands-on activities in the workshop helped me better understand GenAI.	4.48	0.61
3. I like the blended learning mode of this course (self-study and workshop participation).	4.38	0.69
4. Overall, the course is worth taking.	4.50	0.64
5. Overall, the course is well organised.	4.36	0.67
6. I will recommend this course to my colleagues.	4.36	0.73

5. Conclusions and Discussion

This study highlights the positive impact of an AI literacy course on administrative staff, showcasing both motivations and evolving perceptions. The participants were primarily motivated by attention and satisfaction, finding the course content engaging and relevant. Their acceptance of AI tools was high, as they recognised their usefulness in enhancing productivity. Yet, challenges with ease of use indicated the need for user-friendly tools and comprehensive training. Addressing these aspects is essential to promote wider AI adoption at work.

The participants' self-reflections revealed a shift from immediate improvements in work–life balance to a deeper understanding of AI concepts. Although the course provided fundamental AI knowledge, translating it into practical skills remains a challenge. This underscores the need for ongoing support to help participants apply their learning effectively. Additionally, the participants showed growing interest in sharing AI knowledge, suggesting potential for broader community impact. Encouraging this could extend the course's benefits to other professional networks.

Course feedback indicated that while some content was enlightening, it was sometimes too advanced. Future courses should offer tailored content, including field-specific modules and case studies, to better align with professional contexts.

In conclusion, although the course enhanced AI understanding, addressing content customisation and practical application challenges could increase its effectiveness. Conducting a needs analysis before course development would ensure alignment with participants' specific needs, maximising its impact. Future research should explore tailored AI literacy programmes and evaluate long-term outcomes to refine and enhance training approaches.

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