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Impact of AI and Digital Skills Education on University Students' Knowledge and Attitudes toward Generative AI: A Descriptive Evaluation Study

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Abstract: The widespread use of Generative Artificial Intelligence tools among students across different educational levels is reshaping students’ attitudes and educational experiences. These tools are utilized in various fields, including idea generation, writing assistance, and content creation. This study investigates the impact of the Modern Digital Skills course offered by the University of Jordan on students' digital literacy in Generative Artificial Intelligence. This study employed a quantitative approach by conducting pre- and post-course surveys to measure changes in students' knowledge, skills, and attitudes across approximately 1,000 undergraduates from different majors at the university. Key variables include students' understanding of Generative Artificial Intelligence, their confidence in using Generative Artificial Intelligence tools, and their ability to critically evaluate AI-generated content and its ethical implications. The findings indicated whether the course significantly enhances students' knowledge, proficiency, critical thinking, and ethical awareness, while also exploring challenges and opportunities in integrating such a course into the academic curriculum. Ultimately, this study aims to provide insights for curriculum committees and decision-makers at universities in Jordan and the Middle East, emphasizing the importance of designing educational programs that foster essential Artificial Intelligence competencies and prepare students for a professional landscape increasingly shaped by Artificial Intelligence technologies.

Index Terms: Artificial Intelligence, Generative AI, Impact of AI, Digital Skills, Students’ Awareness, Higher Education, Intelligent Software Tools.

1. Introduction

Artificial intelligence (AI) is the ability of computers to effectively and safely accomplish tasks that involve human intelligence in various new situations, based on intelligent entities and trained data. In this sense, programs build scenarios grounded in human rationality through mappings between human behaviors and program input-output patterns, enabling the formation of theoretical models that approximate intelligent reasoning. AI can thus be understood as the study of agents that perceive their environment and take goal-directed actions [1]. The progression of AI has fundamentally transformed the development and deployment of software applications, and in recent years, it has become closely associated with deep learning and generative systems [2]. This advancement of AI marks the beginning of a new era in which human creativity and machine intelligence work collaboratively and adaptively [1].

Among the most transformative developments within this field is Generative Artificial Intelligence (GenAI), a class of systems capable of creating novel text, images, code, and other content based on learned patterns. GenAI technologies such as ChatGPT and DALL·E have rapidly reshaped education, communication, and professional practice, offering unprecedented opportunities for creativity, productivity, and learning [3,4]. However, the pace of adoption has far exceeded formal understanding. Students increasingly use GenAI tools to support academic writing, idea generation, and coding [5], yet their conceptual grasp of underlying mechanisms and ethical boundaries remains uneven [6,7]. This position aligns with global calls for structured AI literacy, defined as the ability to understand, evaluate, and responsibly apply AI systems in academic and professional life.

Despite growing international attention, limited empirical research has examined how structured GenAI education affects students in the Middle Eastern context, where most AI exposure occurs informally. The Modern Digital Skills course at the University of Jordan represents a pioneering regional initiative addressing this gap. Through a dedicated AI module, the course aims to enhance students' conceptual knowledge, confidence, and ethical awareness across all disciplines, including humanities, medical, and scientific domains.

Accordingly, this study investigates the impact of AI and digital skills education on university students' knowledge, attitudes, and intended uses of generative AI. Using pre- and post-course descriptive surveys administered to over 1,000 undergraduates, it explores changes in students' understanding, ethical reasoning, and perceived career relevance following structured instruction. By situating the findings within the broader literature on AI literacy, ethics, and educational reform, the study provides evidence-based insights for policymakers, curriculum designers, and educators in Jordan and beyond, highlighting how higher education can cultivate informed, responsible, and empowered engagement with generative AI.

The remainder of this paper is structured as follows: Section 2 identifies the research gap and defines the study's objectives, emphasizing the need for structured generative AI education within university curricula. Section 3 presents a review of relevant literature on the emergence of generative AI and its educational implications. Section 4 outlines the study's research design, data collection procedures, and survey instruments. Section 5 reports the main findings from the pre- and post-course surveys. Section 6 discusses these findings in light of existing research, highlighting implications for AI literacy and higher education. Finally, Section 7 concludes the paper and offers recommendations for future research.

2. Literature Review

The Generative AI (GenAI) research landscape is rapidly growing in literature, marked by increasing engagement [6], regardless of the varying levels of understanding of its underlying patterns and structures. Recent studies highlighted that students across different educational levels are increasingly using generative AI tools in their academic tasks, such as code and essay generation. However, while usage is on the rise, students' understanding of the underlying mechanisms is inconsistent [5]. Chen et al. [3] emphasized the widespread use of generative AI across various fields, including idea generation, writing assistance, and content creation. In line with this, Fui-Hoon Nah et al. [4] explored the multidimensional applications, challenges, and collaborative potential of Generative AI. They highlighted ChatGPT's versatility across sectors such as education, healthcare, and creative industries, while also addressing concerns related to ethical considerations, accuracy, and the need for effective AI-human collaboration to harness its full potential.

Recent studies have shown that the widespread use of GenAI has forced many educational institutions to limit its usage. Several studies have documented the educators' concerns on the use of GenAI tools in the classroom [8–10]. The major concern is plagiarism [11–15], but other concerns, such as bias [16–18], have also been highlighted. The use of GenAI in the educational sector has been increasingly reported in literature. These studies mainly assess students' learning and understanding of topics [19–23]. Moreover, GenAI is being utilized to automate the marking of students' work in different topics such as essays [24], SQL queries [25], and computer programming [26]. Despite the widespread use of GenAI tools and its positive impact on education, concerns persist regarding their effectiveness and ethical use [27–30].

For example, Ariyo Okaiyeto et al. [31] highlighted the benefits and challenges of Generative AI in education taking into consideration the ethical concerns. They argued that instead of banning AI tools, guidelines must be set, and these tools must be used wisely, while maintaining academic integrity, and instructors need to guide students. Furthermore, Pratschke [32] introduced the important aspects of GenAI in relation to education. They provided an extensive discussion of the transformative potential that GenAI holds in reshaping pedagogical approaches, assessment systems, and learning environments.

Siraj et al. [7] examined student perspectives on generative AI, based on their awareness, preparedness, and concerns. They highlighted that some students were aware of GenAI tools, however they were unaware of the ethical and practical implications. They conducted a concise survey with optional open-ended questions. After examining more than 250 responses, their work provided actionable insights into how students in the GenAI era understand their role in shaping their academic and career paths. In a different context, Abu-Zayed et al. [33] argued that netnography can be employed to evaluate cultural experiences. In contrast, Qasem et al. [34] discovered patterns and implemented predictions based on multiple distributed data sources.

Moreover, Shrivastava and Sun [35] proposed a multi-theory model by integrating three theoretical frameworks: The Technology Acceptance Model (TAM), Protection Motivation Theory (PMT), and Social Exchange Theory (SET), by combining their elements. The aim was to examine the dual outcomes of resistance and acceptance of generative AI among university students. Each theory provides a unique lens to understand the complex interplay of functional, risk, and sociolegal factors in shaping attitudes toward AI technologies. In line with Shrivastava, Su et al. [36] proposed an “IDEE” theoretical framework for educative AI and other generative AI in education, which included identifying the desired outcomes, determining the appropriate level of automation, ensuring ethical considerations, and evaluating effectiveness. Moreover, Duah et al. [37] examined the multifaceted adoption of GenAI in higher education by reviewing interdisciplinary theoretical frameworks from psychology, computer science, and pedagogy.

2.1. Research Gap and Objectives

While recent studies have explored the growing use of generative AI tools among students, most have focused on adoption patterns or ethical concerns rather than examining the relationship between students’ knowledge, experience, and confidence in using these tools responsibly. The literature indicates that students increasingly rely on GenAI to support academic and creative work; however, many do so without fully understanding how these systems function or critically assessing the accuracy and reliability of AI-generated outputs. This gap between widespread usage and limited evaluative competence underscores the urgent need for structured educational interventions.

Accordingly, this study addresses a critical research gap by empirically investigating how a structured AI learning module can influence students’ understanding, attitudes, and intended uses of generative AI. It emphasizes the importance of equipping students with the ability to use GenAI critically, ethically, and effectively rather than only adopting it as a convenience tool. To this end, the study examines the impact of integrating an introductory AI module within the Modern Digital Skills course at the University of Jordan; a course designed to promote responsible and informed engagement with emerging digital technologies.

The primary objectives of this research are to assess students’ baseline knowledge, attitudes, and prior exposure to generative AI before formal instruction, to evaluate the effect of the AI module on students’ self-rated knowledge, ethical perspectives, and confidence in using GenAI tools, and to explore how such curricular integration can influence students’ intended uses of GenAI across academic, personal, and career contexts.

3. Methodology

This study employed a pre–post descriptive survey design to examine university students' knowledge, attitudes, and intended uses of generative artificial intelligence (GenAI) before and after completing an AI module within the Modern Digital Skills course at the University of Jordan. The primary objective was descriptive, with limited inferential analyses conducted to confirm observed changes across samples.

The Modern Digital Skills course (MDS) is a university-wide requirement offered to students across all faculties, with the exception of Information Technology and Engineering students, who instead complete advanced programming and specialized technical courses within their majors. The MDS course aims to enhance students’ digital competencies, featuring a dedicated chapter on Artificial Intelligence that introduces foundational concepts, practical applications, and emerging developments such as generative AI, while emphasizing ethical and responsible use of technology. It adopts experiential and active learning strategies, including interactive lectures and hands-on digital activities, to ensure the development of both conceptual understanding and applied AI skills relevant to the contemporary job market.

3.1. Setting and Participants

All students enrolled in the Modern Digital Skills course were invited to complete the surveys. The pre-survey was administered before the AI module was introduced to investigate students' baseline knowledge of GenAI and any previous usage. The post-survey was distributed after course completion to assess the impact of the AI module. The sample sizes were N = 1,376 for the pre-survey and N = 720 for the post-survey.

3.1.1. Pre-survey Demographics

1. Gender: Female 78.4% (n = 1,079), Male 21.2% (n = 292), Prefer not to say 0.4% (n = 5).
2. **Year of study**: First 26.7% (n = 368), Second 24.4% (n = 336), Third 29.7% (n = 409), Fourth 17.2% (n = 236), ≥5 years 1.9% (n = 27).
3. **College domain**: Humanities 49.9% (n = 687), Medical 27.5% (n = 379), Scientific 22.5% (n = 310).
4. Age: 18-23 years 93.8% (n = 1,291), Other 6.2% (n = 85).

3.1.2. Post-survey Demographics

1. Gender: Female 79.7% (n = 574), Male 20.1% (n = 145), Prefer not to say 0.1% (n = 1).
2. **Year of study**: First 22.6% (n = 163), Second 25% (n = 180), Third 31% (n = 223), Fourth 19.6% (n = 141), ≥5 years 1.8% (n = 13).
3. **College domain**: Humanities 54% (n = 388), Medical 23% (n = 163), Scientific 23% (n = 169).
4. Age: 18-23 years 94.0% (n = 677), Other 6.0% (n = 43).

Colleges were categorized into three domains: 1) Humanities, 2) Medical, and 3) Scientific, ***to facilitate analysis across fields of study.***

3.2. Survey Instrument

Both surveys captured demographics, prior exposure to GenAI, self-rated knowledge, attitudes, frequency of use, perceived benefits and concerns, and planned uses. The instrument consisted of four main sections:

1. **Demographics**: gender, year of study, college domain, and age.
2. **Exposure and usage of GenAI**: prior coursework related to AI/GenAI, experience with GenAI tools, specific tools used, and frequency of use (pre-survey Q8–Q10; post-survey Q8–Q9, Q11).
3. **Knowledge and understanding**: two self-rated items measuring AI and GenAI knowledge on a 5-point Likert scale (1 = No knowledge, 5 = Expert), plus conceptual understanding questions (pre-survey Q11 - Q14).
4. **Attitudes and planned uses**: five attitude items (5-point Likert scale: 1 = Strongly disagree, 5 = Strongly agree) addressing future change, preparedness, cheating (ethical stance), career importance, and job displacement. The post-survey included additional items assessing planned academic, personal, and career uses of GenAI (post-survey Q13 - Q15).

Perceived knowledge and confidence in using technologies are important predictors of behavioral intention to adopt and use digital tools. Foundational models such as the Technology Acceptance Model (TAM) identify perceptions (e.g., perceived usefulness and ease of use) as key determinants of users’ intentions to use technology, demonstrating that confidence and self-assessed knowledge influence adoption behaviors rather than only objective ability measures. Empirical studies have also shown that educators’ and students’ perceptions of generative AI tools significantly relate to their willingness to use them in educational contexts [38].

3.2.1. Comparative Items

To enable descriptive comparison between pre- and post-survey cohorts, two knowledge items were included in both instruments to assess changes in students' knowledge:

1. Pre-survey Q7 ↔ Post-survey Q5: "How would you rate your current understanding of artificial intelligence?"
2. Pre-survey Q15 ↔ Post-survey Q12: "How would you rate your current understanding of generative AI specifically?"

Both items used a five-point Likert scale (1 = No knowledge, 5 = Expert).

Additionally, five attitude statements were measured identically in both surveys using a five-point Likert scale (1 = Strongly disagree, 5 = Strongly agree):

1. **Future change**: Expectations that GenAI will transform how we work.
2. **Preparedness**: Confidence in using GenAI for studying purposes.
3. **Cheating**: Ethical stance on whether GenAI use constitutes academic dishonesty.
4. **Career importance**: Perceived relevance of GenAI for future employability.
5. **Job displacement**: Concerns about potential labor market risks from automation.

3.3. Data Collection Procedure

The pre-survey was administered before the AI module was introduced. The post-survey was distributed after course completion. Participation was voluntary, and responses were collected anonymously.

3.4. Data Analysis

The primary analytic approach was descriptive. Frequencies and percentages were calculated for categorical variables; distributions (counts, percentages) and medians were reported for ordinal Likert items. Graphical representations (bar charts, stacked bar charts) were prepared to summarize tool usage, frequency, and Likert distributions.

3.4.1. Between-Cohort Comparisons

Since responses could not be linked across time points, pre- and post-survey results were analyzed as independent samples in a repeated cross-sectional design. Statistical comparisons were conducted to identify differences in response distributions between cohorts rather than to estimate individual-level change or causal effects.

For items included in both surveys, analyses evaluated whether the distribution of responses differed between the pre- and post-survey groups. Since Likert scale data can be appropriately analyzed as either categorical or ordinal depending on the research question [39,40], two complementary analytical approaches were applied to ensure robustness of interpretation.

First, Pearson Chi-square tests were applied to compare the distribution of responses across the full set of Likert categories, treating Likert data categorically [41]. The chi-square test statistic was calculated as:

$$\chi^2 = \sum_{i=1}^{r}\sum_{j=1}^{c}\frac{(O_{ij} - E_{ij})^2}{E_{ij}} \tag{1}$$

where O_{ij} represents the observed frequency in cell (i, j), E_{ij} represents the expected frequency, r is the number of rows (Likert categories), and c is the number of columns (pre- vs. post-survey groups).

Effect size for chi-square tests was reported using Cramer's V [42]:

$$V = \sqrt{\frac{\chi^2}{N \times (k-1)}} \tag{2}$$

where N is the total sample size (N = 2,096) and k is the smaller of the number of rows or columns. Cramer's V values were interpreted using conventional thresholds for degrees of freedom = 4: small (V = 0.10), medium (V = 0.30), and large (V = 0.50).

Second, Mann–Whitney U tests were conducted to compare the rank distributions of responses between the two independent cohorts while preserving the ordinal nature of Likert-scale data [43]. This non-parametric test evaluates whether responses from one group tend to be systematically higher or lower than those from the other. Two complementary effect size measures were reported for Mann–Whitney analyses:

1. Rank-biserial correlation r_{rb}, which ranges from −1 to +1, and quantifies the degree to which responses in one cohort tend to rank higher than those in the other. Values of approximately 0.10, 0.30, and 0.50 are commonly interpreted as small, medium, and large effects, respectively (Kerby, 2014).
2. Vargha–Delaney's A, which represents the probability that a randomly selected observation from the post-survey cohort has a higher rank than a randomly selected observation from the pre-survey cohort [44]. Values range from 0 to 1, with 0.50 indicating no difference, and values above 0.56 considered small effects, above 0.64 medium effects, and above 0.71 large effects.

All analyses treated the pre-survey (N =1,376) and post-survey (N =720) datasets as independent samples (N =2,096).

3.5. Ethical Considerations

The study followed ethical principles for educational research. Participation was voluntary, and no personally identifying information was collected. Ethical approval and informed consent were obtained from the University of Jordan, with clearance granted by the Deanship of Scientific Research to collect information from participating students.

4. Results

This section presents descriptive findings from the pre- and post-surveys, followed by comparative analyses examining changes in students' knowledge and attitudes toward generative AI after completing the Modern Digital Skills course.

4.1. Pre-Survey Results

4.1.1. Prior Exposure and Usage of GenAI

Despite limited formal training, students demonstrated substantial prior engagement with GenAI tools. Nearly all respondents (96.5%, n = 1,329) reported having never taken any courses related to AI or GenAI. However, 84.9% (n = 1,169) indicated they had used GenAI tools before the course, with ChatGPT being the most commonly reported tool among these users (see Fig. 1). This finding reveals a significant gap between formal education and informal adoption of GenAI technologies.

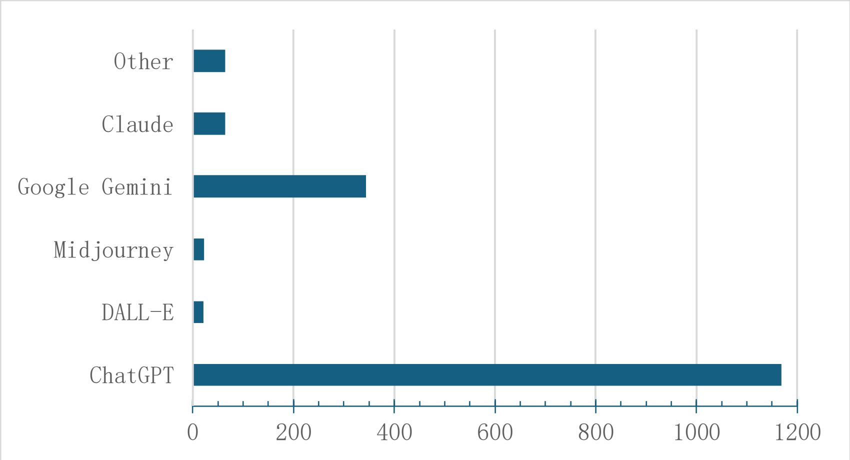

Fig. 1. GenAI tools used by students.

Regarding frequency of use, over two-thirds of students reported using GenAI tools regularly: daily or weekly usage was reported by more than 66% of respondents (See Fig. 2). Notably, usage frequency showed no significant differences across college domains (Humanities, Medical, Scientific), indicating that GenAI engagement transcends disciplinary boundaries and has become widespread even among students in non-technical fields.

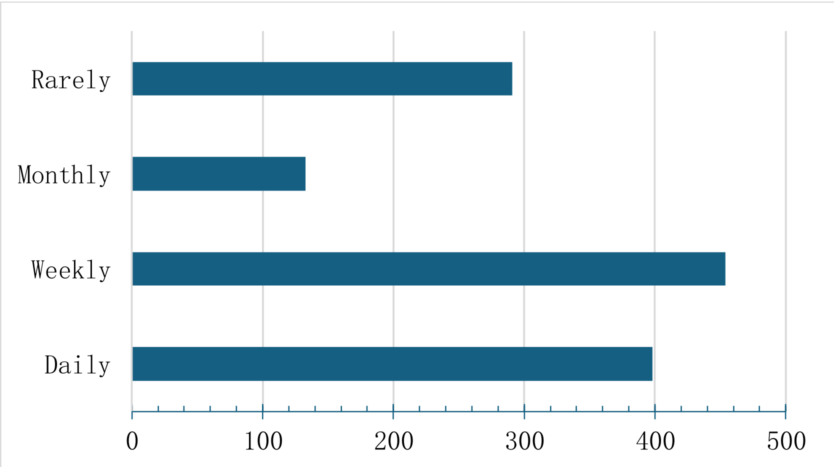

Fig. 2. Frequency of GenAI usage.

4.1.2. Understanding of GenAI

When asked to identify which statement best describes GenAI, the majority of respondents (65.0%, n = 894) correctly selected "a technology that uses algorithms to create new content (text, images, audio) based on the data it was trained on." However, misconceptions were evident among other respondents: 10.8% (n = 149) selected "a technology that relies on predefined rules to answer questions," 7.6% (n = 104) chose "a system that only analyzes and classifies existing data," and 0.9% (n = 12) described it as "a program that only stores information without processing it." Additionally, 15.8% (n = 217) indicated insufficient knowledge to answer. These results suggest that while most students possess accurate foundational understanding, a notable minority demonstrates conceptual gaps that warrant targeted educational intervention.

4.1.3. Perceived Benefits of GenAI

Students identified multiple practical advantages of GenAI tools. The most frequently cited benefits were increased productivity and time savings (66.8%, n = 919) and facilitating access to information (65.0%, n = 895). More than half of respondents (55.3%, n = 761) recognized GenAI's potential for assistance in solving complex problems. Other benefits included enhancing creativity in work (36.7%, n = 505) and improving decision-making processes (33.1%, n = 456). Only a small proportion reported seeing no potential benefits (1.2%, n = 17) or indicated insufficient information to answer (8.4%, n = 116). These findings indicate that students predominantly view GenAI as offering clear practical advantages, particularly in efficiency, information access, and problem-solving domains.

4.1.4. Concerns Regarding GenAI

Despite recognizing benefits, students expressed several concerns about GenAI adoption. Over-reliance on technology emerged as the most frequently cited issue (58.0%, n = 798), followed by privacy and data security concerns (47.5%, n = 654), potential job loss (43.7%, n = 601), and the spread of misinformation (39.6%, n = 545). Ethical concerns about GenAI uses were reported by 30.6% of respondents (n = 421). Only 4.1% (n = 56) indicated having no concerns, while 8.4% (n = 116) reported insufficient information to answer. These results reveal that students maintain a balanced perspective, acknowledging both the practical benefits and potential risks associated with GenAI, particularly regarding dependency, security, employment, and ethical implications.

4.1.5. Anticipated Impact on Future Employment

Students held diverse views regarding GenAI's impact on their future careers. The largest proportion (31.7%, n = 437) anticipated that GenAI would enhance their skills and increase productivity. However, 25.5% (n = 351) expressed concern that it may replace some of their job tasks, while 17.7% (n = 244) believed it would not have a significant impact on their jobs. Fewer respondents anticipated that GenAI would create new opportunities in their field (12.8%, n = 176), have a negative impact on humans (9.8%, n = 135), or completely change the nature of their current job (2.4%, n = 33). These findings suggest that while many students view GenAI optimistically as a tool for skill enhancement, a substantial number also recognize potential disruptions to their future employment.

4.2. Post-Survey Results

4.2.1. Changes in Perception and Confidence

Following course completion, more than half of the students (56%) reported that their perception of GenAI had changed extremely or somewhat. Additionally, 38% indicated increased confidence in using GenAI tools. These findings indicate that many respondents reported changes in their perceptions and confidence following the course.

4.2.2. Planned Academic Uses

When asked how they plan to incorporate GenAI tools in academic work, students identified several applications. The most common response was for learning and skill development (38%, n = 274), followed by research and data analysis (34%, n = 245), and writing and content creation (17%, n = 119). A minority indicated they were not planning to use such tools (10.0%, n = 74), while very few selected "other" (1%, n = 8). These results suggest that students primarily envision GenAI as supporting learning and research activities rather than replacing traditional academic practices.

4.2.3. Planned Personal Uses

For personal projects, the largest proportion of respondents reported planning to use GenAI for productivity and organization (40%, n = 285), followed by creative projects such as art, music, or writing (26%, n = 185), and experimentation and exploration (21%, n = 154). A smaller group indicated no plans to use GenAI personally (12%, n = 88), with very few selecting "other" (1%, n = 8). This indicates students are open to applying GenAI beyond formal academic contexts, particularly for enhancing personal productivity and creative endeavors.

4.2.4. Planned Career Uses

Regarding future career applications, the most frequently chosen option was to develop new skills for career growth (44%, n = 314), followed by enhancing job performance (32%, n = 227), and exploring AI-related career opportunities (11%, n = 79). A minority reported not planning to use GenAI in their careers (13%, n = 95), with very few selecting "other" (0.7%, n = 5). These responses suggest students perceive GenAI as valuable for professional development and career advancement.

Across all three contexts: 1) academic, 2) personal, and 3) career, students demonstrated generally positive orientations toward GenAI adoption. The primary intended uses centered on learning support, productivity enhancement, creativity, and professional skill development, with only small minorities across contexts reporting no plans to use such tools.

4.3. Between-Cohort Differences: Pre- and Post-Survey

4.3.1. Differences in Self-Rated Knowledge

Two knowledge items were measured in both surveys: (1) understanding of artificial intelligence generally, and (2) understanding of generative AI specifically. Both were assessed using five-point Likert scales (1 = No knowledge, 5 = Expert).

For AI knowledge, chi-square analysis revealed a statistically significant difference in response distributions between cohorts, $\chi^2(4, N = 2{,}096) = 166.82$, $p < .001$, with a medium effect size (Cramer's V = 0.28). Similarly, the post-survey cohort reported higher levels of understanding of GenAI, $\chi^2(4, N = 2{,}096) = 123.41$, $p < .001$, Cramer's V = 0.24. Mann–Whitney U tests indicated that responses from the post-survey cohort tended to rank higher than pre-survey responses for both AI knowledge (U = 648,243.5, $p < .001$, r_rb = 0.31, A = 0.65) and GenAI knowledge (U = 630,882.5, $p < .001$, r_rb = 0.27, A = 0.64).

These findings indicate that the course intervention produced statistically significant and practically meaningful improvements in self-reported knowledge (see Table 1). The Vargha-Delaney A statistic suggests that a randomly selected post-survey student had approximately a 65% probability of rating their AI knowledge higher than a randomly selected pre-survey student, and a 64% probability for GenAI knowledge. These effect sizes (A > 0.64) represent medium to large effects [44], indicating substantial educational impacts.

Table 1. Changes in Self-Rated Knowledge (Pre- vs. Post-Survey).

Measure	**χ^2 (df, N)**	**p-value**	**Effect size (Cramer's V)**	**Mann–Whitney U (p-value)**
AI understanding	$\chi^2(4, 2{,}096) = 166.82$	< .001	V = 0.28 (medium)	U = 648,243.5, p < .001
Gen AI understanding	$\chi^2(4, 2{,}096) = 123.41$	< .001	V = 0.24 (medium)	U = 630,882.5, p < .001

Note. Self-rated knowledge responses were distributed toward higher categories in the post-survey cohort compared with the pre-survey cohort. Effect sizes indicate that a randomly selected respondent from the post-survey cohort had approximately a 65% (AI) and 64% (GenAI) probability of reporting higher knowledge than a respondent from the pre-survey cohort. Because samples were independent, these findings represent between-cohort differences rather than measured individual change.

4.3.2. Differences in Attitudes between Cohorts

The following five attitude statements were measured in both surveys using five-point Likert scales (1 = Strongly disagree, 5 = Strongly agree) (see Table 2)

1. Future Change: Students already strongly believed that GenAI would reshape future work before the course, and the post-survey cohort showed slightly stronger agreement; this difference was statistically significant, $\chi^2(4, N = 2{,}096) = 9.80$, $p = .044$, V = 0.07. This indicates a small effect size in the difference between cohort responses.
2. Preparedness: Agreement with the statement regarding preparedness to use GenAI in studies increased significantly, $\chi^2(4, N = 2{,}096) = 13.23$, $p = .010$, V = 0.08. This reflects higher reported preparedness in the post-survey cohort.
3. Cheating: Attitudes toward the statement that using GenAI constitutes cheating shifted slightly toward neutrality; $\chi^2(4, N = 2{,}096) = 11.05$, $p = .026$, V = 0.07. Responses showed a small but statistically significant redistribution toward neutral categories, indicating a modest difference in how the two cohorts positioned their views on this issue.
4. Career Importance: The most substantial attitudinal change occurred in the recognition of GenAI's relevance for future careers; $\chi^2(4, N = 2{,}096) = 39.38$, $p < .001$, V = 0.14. A moderate distributional difference was observed for recognition of GenAI's relevance to future careers, with the post-survey cohort more frequently selecting higher agreement categories.
5. Job Displacement: Concern about GenAI causing job loss showed no significant overall change; $\chi^2(4, N = 2{,}096) = 7.49$, $p = .112$. While a slight increase in agreement was observed, many students continued to select neutral responses, indicating ongoing uncertainty. No statistically detectable difference in distributions was observed between cohorts.

Table 2. Changes in Attitudes Toward GenAI (Pre- vs. Post-Survey).

Attitude Domain	χ^2 (df, N)	p-value	Effect size (Cramer's V)
1. Future change (GenAI will reshape work)	$\chi^2(4, 2{,}096) = 9.80$	0.044	V = 0.07 (small)
2. Preparedness to use GenAI	$\chi^2(4, 2{,}096) = 13.23$	0.01	V = 0.08 (small)
3. Cheating in academics	$\chi^2(4, 2{,}096) = 11.05$	0.026	V = 0.07 (small)
4. Career importance	$\chi^2(4, 2{,}096) = 39.38$	< .001	V = 0.14 (moderate)
5. Job displacement concerns	$\chi^2(4, 2{,}096) = 7.49$	0.112	-

Note. Several items showed small to moderate distributional differences between cohorts, while concern about job displacement did not differ statistically. These comparisons reflect independent cross-sectional samples.

5. Discussion

This study examined university students' knowledge, attitudes, and intended uses of generative AI before and after completing an AI module integrated into the Modern Digital Skills course at the University of Jordan. The findings reveal several descriptive patterns regarding informal GenAI adoption and differences observed between the pre- and post-survey cohorts.

5.1. The Gap between Informal Use and Formal Education

One of the most striking findings was the substantial disconnect between students' extensive informal GenAI use and their lack of formal education in this area. While 96.5% of students had never taken an AI-related course, 84.9% reported prior GenAI tool use, with ChatGPT being universally adopted among users. This pattern reflects broader trends in technology adoption, where accessible consumer-facing tools achieve rapid diffusion independent of institutional support or structured learning. The widespread daily and weekly usage (over 66%) across all college domains (Humanities, Medical, and Scientific) demonstrates that GenAI has transcended disciplinary boundaries and become integrated into students' everyday practices.

However, this informal adoption occurred alongside notable knowledge gaps. While 65% correctly identified GenAI's core functionality, nearly 20% selected incorrect definitions and 15.8% admitted insufficient knowledge to answer. This suggests that students were learning through trial and error, potentially developing misconceptions or limited understanding of how these tools work, their limitations, and appropriate use cases. The post-survey cohort reported higher self-rated knowledge levels, although this quasi-experimental design limits the ability to attribute these differences solely to the course intervention.

5.2. Educational Impact: Knowledge Gains

Comparative analyses identified statistically significant differences in self-reported knowledge distributions between cohorts. Both general AI knowledge and GenAI-specific knowledge showed medium effect sizes (Cramer's V = 0.28 and 0.24, respectively), with post-survey students having approximately 64-65% probability of rating their knowledge higher than pre-survey students. These effect sizes, while moderate, represent moderate between-cohort differences, particularly considering the brief intervention period within a broader digital skills curriculum.

The improvement in self-rated knowledge aligns with students' self-reported perception changes: 56% indicated their perception of GenAI had changed after the course, and 38% reported increased confidence in using GenAI tools. These findings suggest that respondents in the later cohort reported greater familiarity with GenAI concepts, leading to a more structured understanding and potentially equipping them to use GenAI more effectively and critically.

5.3. Shifting Attitudes: From Concerns to Opportunities

The pre-survey revealed that students held balanced but somewhat cautious views of GenAI. While they recognized clear benefits, particularly productivity gains (66.8%), information access (65.0%), and problem-solving assistance (55.3%), they also expressed significant concerns about over-reliance (58.0%), privacy (47.5%), job loss (43.7%), and misinformation (39.6%). This dual awareness reflects mature thinking about technology's potential risks and rewards.

Following the course, several distributional differences between cohorts were observed. Most notably, recognition of GenAI's career importance showed the largest effect size (V = 0.14), indicating students developed stronger conviction that AI literacy would matter for their professional futures. This pattern indicates stronger agreement within the post-survey cohort, as employability concerns motivate skill development and career preparation. The course also increased students' sense of preparedness to use GenAI in their studies, suggesting they gained not only knowledge but also practical confidence.

Interestingly, attitudes toward GenAI as cheating shifted slightly toward neutrality. Rather than representing confusion, this likely reflects more sophisticated ethical reasoning. One possible interpretation is that respondents viewed GenAI use as involving contextual judgments about appropriate application rather than binary right-wrong distinctions. This interpretation is supported by the fact that students plan to use GenAI primarily for learning and skill development (38%) and research support (34%), not as shortcuts. The nuanced view of ethics underscores the need for clear institutional guidelines on acceptable GenAI use in academic settings, as many studies have recommended.

5.4. Persistent Concerns About Employment

Despite increased recognition of GenAI's career relevance, concerns about job displacement remained statistically unchanged after the course. Before instruction, 43.7% worried about potential job loss, 25.5% feared task replacement, and only 31.7% emphasized skill enhancement. After the course, anxiety levels did not significantly decrease, and many students continued selecting neutral responses, indicating ongoing uncertainty.

This persistence suggests that employment concerns operate at a deeper level than knowledge or skill-related attitudes. Students may intellectually understand GenAI's potential to augment human capabilities while simultaneously harboring visceral anxieties about labor market disruption. These fears are not unfounded; extensive research documents automation's uneven impacts across sectors and skill levels. The diversity of majors represented in this study may have contributed to mixed results, as students in different disciplines likely perceive GenAI's risks differently. Medical and scientific students might anticipate enhanced capabilities, while humanities students may worry about automation of creative or analytical tasks.

Educational interventions alone may be insufficient to address employment anxieties that reflect broader socioeconomic uncertainties. Addressing these concerns may require complementary approaches, including career counseling, emphasis on uniquely human skills that complement AI, and preparation for adaptive career trajectories in rapidly changing labor markets.

5.5. Intended Uses: Learning, Productivity, and Growth

The post-survey revealed students' intended GenAI applications across academic, personal, and career contexts. In academic settings, learning and skill development (38%) and research support (34%) were primary intended uses, with relatively few planning to use GenAI for writing and content creation (17%). This pattern suggests students view GenAI as a learning aid rather than a replacement for their own thinking and work.

For personal projects, productivity and organization (40%) topped the list, followed by creative applications (26%) and experimentation (21%). The emphasis on productivity aligns with pre-survey findings identifying time savings as GenAI's primary benefit. Students appear poised to integrate these tools into everyday life beyond formal educational requirements.

Career-related intentions centered on skill development (44%) and performance enhancement (32%), with smaller proportions interested in exploring AI-related career opportunities (11%). These findings reinforce the interpretation that students increasingly recognize AI literacy as a professional competency rather than a specialized technical skill relevant only to certain fields.

Notably, only 10-13% across contexts reported no plans to use GenAI, indicating broad acceptance and anticipated adoption. This widespread openness creates opportunities for educators and institutions to shape responsible, effective, and ethical GenAI use through ongoing guidance and support.

5.6. Implications for Higher Education

These descriptive findings suggest several considerations for curriculum development and institutional policy. First, the gap between informal use and formal education suggests that universities must move beyond merely introducing AI topics toward providing structured, critical education about these technologies. Students are already using GenAI; the question is whether they will do so with understanding, discernment, and awareness of limitations.

Second, the significant knowledge gains and attitude shifts following a relatively brief intervention suggest that such modules may play a role in supporting AI literacy, though causal effects cannot be established in this study. Integrating AI content into required courses like digital skills ensures broad reach across disciplines, helping students develop foundational understanding regardless of their major.

Third, the persistence of employment concerns despite increased knowledge suggests that AI education should explicitly address labor market implications, emphasizing not only technical capabilities but also the development of adaptive, complementary human skills. Preparing students for AI-augmented careers may require ongoing support beyond single course modules.

Fourth, the nuanced shift in attitudes toward GenAI ethics highlights the need for clear institutional guidelines on acceptable use in academic contexts. As students develop more sophisticated understanding, they require corresponding guidance about boundaries, attribution, and appropriate application in different academic situations.

Finally, students' intended uses across learning, productivity, and career contexts suggest that GenAI integration into higher education should be multifaceted, addressing not only technical skills but also critical evaluation, ethical reasoning, and strategic application across diverse domains.

5.7. Limitations

Several limitations should be acknowledged. The study employed a pre-post design with independent samples rather than matched participants, limiting causal inference about individual-level change. Because the samples were independent and no control group was available, observed differences cannot be attributed solely to the instructional module and may reflect cohort composition or external exposure to GenAI. The voluntary nature of survey participation may have introduced self-selection bias, potentially over representing students already interested in or knowledgeable about GenAI. Self-reported measures of knowledge and attitudes may not fully correspond to actual understanding or behavior. The study was conducted at a single institution in a specific cultural context, which may limit generalizability to other settings. Finally, the relatively brief follow-up period captured immediate post-course effects but not long-term retention or behavioral change. Additionally, the drop from 1,376 pre-survey to 720 post-survey respondents may have introduced non-response bias, as students completing the post-survey could differ systematically from those who did not.

5.8. Future Research Directions

Future research should employ longitudinal designs tracking individual students over time to better establish causal relationships between instruction and outcomes. Studies should also incorporate objective knowledge assessments alongside self-reports to validate learning gains. Investigation of how students actually apply GenAI tools in their academic work, personal projects, and eventually careers would provide valuable insights into the translation of intentions into practice. Cross-cultural and cross-institutional comparisons would clarify how context shapes GenAI adoption and learning. Finally, research examining optimal pedagogical approaches for AI literacy education could inform curriculum development and instructional design.

6. Conclusion

This study provides compelling evidence that even brief, integrated AI education can significantly enhance university students' knowledge, confidence, and attitudes toward generative artificial intelligence. Students initially entered the course with considerable informal exposure to GenAI tools but limited conceptual understanding and ethical awareness. Following participation in the Modern Digital Skills course, their self-rated knowledge, preparedness, and recognition of AI's professional relevance improved markedly. These findings demonstrate that structured, curriculum-embedded instruction can bridge the gap between casual AI use and informed, responsible engagement.

Although concerns about job displacement and automation persisted, students developed more nuanced ethical perspectives, shifting from categorical judgments to context-dependent reasoning about when and how GenAI can be used appropriately. This maturation in ethical understanding, coupled with students' expressed intentions to apply GenAI across academic, personal, and career contexts, highlights the transformative potential of well-designed AI literacy initiatives.

As GenAI tools continue to evolve and integrate nearly every aspect of modern life, higher education institutions have a critical role in ensuring that students develop not only technical familiarity but also critical evaluation skills, ethical reasoning, and adaptive digital competence. The results of this study suggest that integrating AI literacy into core university curricula represents an effective strategy for preparing students for an AI-augmented professional future.

Rather than viewing generative AI as a threat to academic integrity or employment stability, universities can position it as an educational opportunity, a catalyst for developing new literacies, encouraging critical reflection on technology, and empowering students to navigate and shape the future of intelligent systems with confidence, responsibility, and creativity.

All the Declarations and Statements

Author Contributions Statement

Esra Alzaghoul – Performed the comprehensive literature review and prepared the development and formatting of the template, including author information and profiles. Ensured clarity and coherence, and helped coordinate deadlines.
Abdelbaset Assaf – Proposed the research idea and methodology, performed data analysis, and reported results.
Tahani Al-Khatib – Wrote and revised the discussion section, formatted and styled the manuscript according to journal guidelines, managed and verified references, organized tables, and oversaw the overall manuscript presentation.
Rana Yousef – Conceptualized the study, identified and articulated the research gap, and drafted the introduction and conclusion to ensure alignment between the study's motivation, objectives, and overall narrative structure.

All authors have read, reviewed, and agreed to the published version of the manuscript.

Conflict of Interest Statement

The authors declare no conflicts of interest.

Funding Declaration

None.

Data Availability Statement

The analyzed datasets are available upon request.

Ethical Declarations

Ethical approval is granted from the research IRB committee at the University of Jordan/Deanship of Scientific Research.

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Declaration of Generative AI in Scholarly Writing

Artificial intelligence tools were used only for language refinement and phrasing improvement. No AI tools were used for data analysis, interpretation, or generation of scientific content.

Abbreviations

The following abbreviations are used in this manuscript:

AI - Artificial Intelligence
GenAI - Generative Artificial Intelligence
STEM - Science, Technology, Engineering, and Mathematics
MDS - Modern Digital Skills course
TAM - Technology Acceptance Model

Appendix A/B/C…, with appendix title

None.

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