Krisnadana Journal (Journal of Computers, Control Systems & Networks)
Vol 5, Issue 3, May 2026, pp. 632-652
https://doi.org/10.58982/ttjd4r39

E-ISSN: 2808-35 63
P-ISSN: 2808-3520

The Use of Artificial Intelligence-Based Learning Tools to Enhance Students' Employment Readiness in the Digital Age

Ayu Gede Willdahlia[1*], Aniek Suryanti Kusuma [2] , Desak Made Dwi Utami Putra[3] , Ni Kadek Nita Noviani Pande[4]

[1*,2,3,4]Institut Bisnis dan Teknologi Indonesia, Denpasar, Indonesia
*willdahlia@instiki.ac.id**

ARTICLE INFO

Article history:
Received 12 June 2026
Revised 16 July 2026
Accepted 17 July 2026

Keywords:
Artificial Intelligence;
AI Tools;
Employability Skills;
Higher Education;
Digital Era

ABSTRACT

This study examines the utilization of Artificial Intelligence (AI)-based learning tools, such as ChatGPT, Grammarly, and Quillbot, in improving student employability in the digital era. The rapid development of technology has brought significant transformation to the education sector, where graduates are now required to possess a broader range of skills beyond academic knowledge, including critical thinking, communication, collaboration, and digital literacy. This research addresses the existing gap between the use of AI as a technical aid and its potential to systematically develop these essential competencies. A quantitative research approach was employed with a purposive sample of 150 active students from the Indonesian Business and Technology Institute (INSTIKI) who actively use AI tools in their academic activities. Data was collected via a Likert-scale online questionnaire and analyzed using descriptive and inferential statistics, including correlation and simple linear regression. The findings indicate that students frequently use AI tools and perceive them as beneficial to their learning process. Overall, the analysis reveals that the use of these AI tools has a positive correlation with students' employability. The strategic integration of AI serves as a catalyst for fostering skills highly relevant to the demands of the modern job market, particularly in digital literacy, critical thinking, and collaboration. The study concludes that AI is not merely a technical tool, but a strategic partner in holistically preparing students for future professional challenges.

1. Introduction

Advances in information and communication technology have brought about significant transformations across various sectors of life, including the world of education. One of the most notable innovations is the use of artificial intelligence (AI)-based learning tools such as ChatGPT, Grammarly, Quillbot, and various similar platforms. These tools not only offer ease of access to information but also support students in carrying out their academic activities more efficiently and independently, such as writing essays, drafting reports, translating texts, and analyzing data[1].

The use of AI technology in higher education presents significant opportunities for improving the quality of learning. Students can develop critical and creative ideas through interaction with AI systems capable of providing instant and personalized feedback. Additionally, AI enables more effective personalized learning, allowing students to learn according to their own styles and paces[2] . Thus, AI serves not only as a tool but also as a partner in a deep and continuous learning process.

However, beyond the academic realm, today's job market demands graduates with competencies that extend far beyond mere mastery of course material. Employability skills—such as communication, critical thinking, problem-solving, collaboration, and digital literacy—are key to entering a dynamic and competitive global labor market[3] . Therefore, higher education must systematically integrate the development of these competencies into its curriculum.

In this context, the use of AI-based educational technology can be an effective strategy for developing students' employability skills. Through interaction with AI, students are trained to think reflectively, evaluate various alternative solutions, and communicate ideas in a structured and logical manner. The integration of this technology also opens opportunities for project-based learning and online collaboration that closely resemble real-world work situations, thereby strengthening their readiness to face future professional challenges[4] .

Although the use of AI-based technology in higher education is becoming increasingly widespread, there remains a gap in the optimal integration of this technology with the development of work readiness competencies. Many educational institutions utilize AI merely as a technical tool in the learning process, without accompanying it with structured pedagogical strategies to cultivate the soft skills required in the workplace. In fact, research indicates that an educational approach that integrates technology with the development of cognitive and social skills is far more effective in preparing students to face the challenges of the professional world[4], [5] . Therefore, it is crucial to evaluate not only the extent to which technology is used but also how it is utilized within the context of transformative learning.

Through learning, in preparation for the future of work, higher education must be able to produce graduates with a balance between technological proficiency and higher-order thinking skills. If AI-based tools are used only to mechanically complete tasks, opportunities for developing critical thinking and problem-solving abilities may be missed. Therefore, a systematic and strategic pedagogical approach is needed so that technology not only accelerates the process but also deepens understanding and strengthens students' competencies comprehensively[6] .

2. Method

Theoritical Foundation

Educational Technology and AI in Learning

Educational technology is a field that continues to evolve alongside advancements in information and communication technology (ICT). This technology encompasses the use of various media, software, and digital approaches designed to enhance the effectiveness and efficiency of the learning process. Educational technology involves the application of scientific principles and technological tools to design, implement, and evaluate learning systems so they are more structured and adaptive to students' needs. The use of this technology includes visual media, online learning, and learning management systems (LMS) that facilitate real-time and asynchronous interaction between educators and learners[7] .

In recent decades, the presence of artificial intelligence (AI) in the world of education has become one of the most significant forms of digital transformation. AI in the context of learning refers to computer systems capable of simulating human cognitive processes, such as recognizing patterns, making predictions, and providing automatic feedback. One of the main benefits of AI in education is its ability to provide adaptive learning—that is, tailoring learning materials or methods based on each student's abilities, learning styles, and pace[4] . For example, systems like ChatGPT can be used to answer questions, recommend references, or help students organize their ideas independently, thereby supporting more personalized and self-directed learning.

In addition, AI also plays a crucial role in the learning assessment process. Intelligent algorithms enable the system to automatically grade answers, provide immediate feedback, and even detect recurring error patterns among students to subsequently suggest appropriate learning interventions[1] . This technology expands educators' capacity to gain a deeper understanding of students' learning needs without having to grade each assignment manually. Furthermore, the use of applications like Grammarly and Quillbot demonstrates how AI can help students improve their academic communication skills by providing suggestions for improving writing style, sentence structure, and text cohesion.

The integration of AI into educational technology also creates opportunities to promote data-driven learning. Through learning activity tracking systems, AI-based platforms can provide analytical insights into student learning behaviors and predict learning outcomes. Consequently, educators and educational institutions can make more informed decisions when designing effective learning interventions[8] . AI-powered educational technology is not merely a technical tool but also a strategic partner in creating smarter, more efficient, and contextually relevant learning experiences.

ChatGPT

ChatGPT is an AI-based language model developed by OpenAI and designed to generate text, answer questions, and help users understand concepts across various fields of study. In an educational context, ChatGPT functions as an intelligent tutoring system (ITS)—an AI-based system capable of providing immediate feedback to users, explaining course material, and facilitating discussions much like a virtual tutor[1] . These functionalities greatly assist students in understanding complex topics, developing arguments, and independently exploring ideas. Its primary advantages are flexibility in timing and scalability, enabling learning to occur anytime and anywhere.

The use of Artificial Intelligence (AI)-based technology in higher education has shown significant growth. Most research still focuses on AI as a technical tool to enhance the efficiency of academic tasks[1][2] . Empirical studies examining the contribution of AI utilization to the multidimensional development of employability skills remain limited. Employability frameworks such as CareerEDGE and USEM have not been widely used to link AI usage with student employability. The context of higher education in Indonesia, particularly at technology-based institutions like INSTIKI, has also not been extensively explored. This study aims to address this gap by comprehensively analyzing the relationship between AI utilization and student employability.

From a constructivist perspective, ChatGPT can be viewed as a tool that supports self-regulated learning (SRL), which is a learning process controlled by the learners themselves through planning, monitoring, and evaluating their understanding[9] . By using ChatGPT, students can ask questions repeatedly, seek clarification, and test their understanding of a subject without pressure from the classroom environment. This fosters a more personalized and reflective learning experience. However, it is important for students to possess strong digital literacy skills so they can filter, verify, and evaluate information obtained from AI systems like ChatGPT.

Grammarly

Grammarly is an AI-based application used to improve writing quality through corrections in grammar, spelling, punctuation, and writing style suggestions. This application functions as a writing assistant that provides real-time feedback, allowing students to learn from the mistakes they make while writing[10] . Grammarly not only corrects errors but also explains why a change is necessary, thereby indirectly educating users on how to improve their academic writing skills.

In the context of cognitive apprenticeship theory, Grammarly serves as a tool that demonstrates the expert thinking process involved in crafting grammatically and rhetorically correct writing[11] . By reviewing the corrections and explanations provided by Grammarly, students gradually learn from concrete examples and can internalize patterns of good writing. This process helps them develop metacognition—the ability to reflect on and control their thought processes while writing—which is crucial in the context of higher education.

Quillbot

Quillbot is an AI-based paraphrasing tool that helps rephrase sentences to avoid plagiarism and improve clarity and linguistic variety in writing. In the academic world, the ability to paraphrase accurately is essential, especially when citing literature or restating ideas in one's own words. Quillbot supports this process by offering multiple paraphrased versions to choose from, enabling students to gain a deeper understanding of sentence structure and meaning[12] .

From the perspective of scaffolding theory in learning, Quillbot functions as a tool that provides temporary support for complex writing tasks. When students do not yet have the full ability to rephrase sentences, this tool offers alternatives that can be analyzed and studied. Over time, this support can be reduced as students' independent writing skills improve[13] . Thus, Quillbot is not merely an automation tool but also has the potential to serve as a medium for linguistic and rhetorical learning when used critically and reflectively.

Student Employability Skills

Employability is broadly defined as a combination of knowledge, skills, and personal attributes that significantly enhance graduates' prospects for securing and retaining employment, as well as for pursuing a sustainable career[14] . Ideally, employability is integrated into the curriculum, not merely viewed as the final outcome of the educational process. Through the Learning & Employability series, the USEM (Understanding, Skills, Efficacy, Metacognition) conceptual framework is introduced, positioning conceptual understanding, skills, self-efficacy beliefs, and metacognition as interrelated elements in shaping graduates' employability, emphasizing the need for evidence-based assessment of these outcomes[14] .

To clarify the pathway for developing work readiness, Pool and Sewell (2007) proposed the CareerEDGE model. This model emphasizes five elements: career development learning, experiences (academic and non-academic), subject-specific knowledge/skills, generic skills, and emotional intelligence. A distinctive feature of CareerEDGE is its emphasis on self-reflection and self-evaluation to enhance self-efficacy and career confidence, ensuring that graduates possess not only technical competencies but also the psychological readiness to enter the job market[15].

Empirically, learning approaches that integrate work-based experiences (work-integrated learning—WIL) show a positive correlation with increased employability. Systematic reviews demonstrate that workshop- or project-based soft skills interventions can enhance generic competencies, career outcomes, and even indicators of student well-being. Data from the World Economic Forum's "The Future of Jobs 2025" report further underscores the shifting demand for skills, positioning analytical thinking and technology/AI literacy as core competencies. This signals that higher education institutions should prioritize curricula responsive to labor market dynamics[16].

The Relationship Between Educational Technology and Competency Development

Previous studies have consistently shown that digital learning technologies are effective in improving learning outcomes, particularly when integrated within a robust pedagogical design framework, supported by instructors, and backed by adequate infrastructure. For example, a comprehensive meta-analysis by the U.S. Department of Education found that online learning models, particularly blended learning formats, tend to yield significantly better performance compared to purely face-to-face instruction[17].

The Digital Education Outlook 2023 emphasizes that the quality of the digital ecosystem is fundamentally determined by instructional design and governance that facilitate active and measurable learning practices. These findings underscore that digital technology functions not merely as a medium, but as an enabler to enhance the quality of learning interactions—a crucial foundation for paving the way toward AI-driven personalized learning[18].

Personalization facilitated by intelligent tutoring systems (ITS) and educational AI applications has been shown to provide substantial learning benefits[19] . Moderate to large effect sizes are observed when instruction is tailored to students' individual needs and progress. This effectiveness is primarily driven by AI's ability to provide adaptive feedback and dynamically organize learning materials. In line with this empirical evidence, a U.S. Department of Education report (2023) recommends the responsible use of AI to strengthen formative assessment and support student-centered learning. Thus, data-driven and AI-based personalization expands opportunities for instructional differentiation, encouraging further exploration of various other digital technologies that can also enhance competencies[18] .

These technologies include personalized/adaptive learning, learning analytics, and immersive Virtual Reality (VR) simulations. A study by the RAND Corporation on personalized learning practices in dozens of schools showed a significant improvement in students' math and reading achievement compared to a control group. Additionally, a meta-analysis of learning analytics-based interventions (2025) reported moderate effects on learning outcomes when process data was used to provide actionable feedback and motivational support. Meanwhile, a recent meta-analysis indicates that VR has a positive impact on the mastery of practical skills in science and engineering, particularly when simulations are designed authentically and assessed based on performance[2] .

Table 1. Summary of Educational Technology Meta-Analysis Effects

Technology / Intervention	Primary Sources	Average Effect Size	Key Moderating Factors
Online Learning vs. Face-to-Face Learning	U.S. Department of Education (2009)	+0.24	Additional learning time; type of instruction (purely online vs. blended)
Intelligent Teaching System (ITS)	Ma et al. (2014)	g = 0.42 (vs. teacher) g = 0.57 (vs. non-ITS computer) g = -0.11 (vs. human instruction)	Type of treatment comparison received by students
Learning Analytics (LA)	Liu, Liu, & Xu (2025)	0.359	Education level (significant effect in higher education, not in K-12); dashboard type (prescriptive > descriptive/predictive)
Virtual Reality (VR)	Chen et al. (2024)	g = 0.85	Level of engagement (cognitive > affective); educational level (higher education > K-12); type of knowledge (procedural > declarative)

Based on a synthesis of data from various meta-analyses, it can be concluded that digital learning technologies and artificial intelligence (AI) have significant potential to improve learning outcomes and, implicitly, contribute to students' employability. The effectiveness of these technologies is highly dependent on the implementation context, where online and blended learning demonstrate superior results compared to purely face-to-face instruction, especially when accompanied by additional study time and enriched instructional elements. Specifically, *intelligent tutoring systems* (ITS) have proven effective in personalizing learning and even show results comparable to individual instruction by humans. Meanwhile, learning analytics generates positive impacts, particularly at the higher education level and when using prescriptive dashboards that provide actionable guidance. Finally, virtual reality (VR) significantly enhances student engagement and is highly effective in developing practical skills, which are essential for the workforce. Therefore, this report confirms that the strategic integration of AI-based learning tools not only improves academic outcomes but also serves as a catalyst for fostering skills and competencies relevant to the demands of the digital-age job market[20] [18] .

Table 2. Skills Needed for the Future Workforce

Skill Categories	Key Skills
Technical / Digital	AI Literacy, Big Data, Cybersecurity, Data Analysis, Ability to Interact with Computers
Human-Centered / Cognitive	Analytical Thinking, Creative Thinking, Resilience, Flexibility, Agility, Curiosity, Communication
Foundational Skills	Text Comprehension, Mathematical Reasoning, Social-Emotional Skills, Data Literacy, Willingness to Act

Based on the data presented in Table 2, it can be concluded that work readiness in the digital age demands a comprehensive blend of skills that goes beyond technical competencies alone. Reports from the World Economic Forum and the OECD emphasize that the future job market requires mastery of technical/digital skills such as AI literacy, data analysis, and computer interaction skills. However, equally crucial are human-centered and cognitive skills, such as analytical thinking, creative thinking, resilience, and communication, which cannot be replicated by machines. Furthermore, these reports also emphasize the importance of foundational skills, including text comprehension and mathematical reasoning, as the foundation for lifelong learning. Therefore, research on the utilization of AI-based learning tools is highly relevant because this technology can serve as a catalyst for fostering the full spectrum of these skills, thereby holistically enhancing students' employability to meet the demands of an ever-changing job market[16] .

Research Method

Population and Sample

The population in this study consists of active students from several study programs at the Indonesian Institute of Business and Technology (INSTIKI). The research sample comprises 150 students. Sampling was conducted using the purposive sampling method, in which respondents were selected based on specific criteria, namely students who actively use AI-based learning tools in their academic activities.

Data Collection Techniques

Primary data was collected using an online questionnaire designed with Likert-scale statements. This questionnaire was designed to measure three main aspects: (1) the level of AI tool utilization, (2) students' perceptions of the tools' contribution to learning, and (3) students' level of work readiness. Additionally, interviews may be conducted optionally to enrich the quantitative data with deeper qualitative insights regarding students' experiences.

Data Analysis Techniques

The collected data will be analyzed using statistical software, such as SPSS (Statistical Package for the Social Sciences). The analysis process will be divided into two main stages:

Descriptive Statistical Analysis

This stage aims to describe the characteristics of the data and research variables. The analysis will include calculations of the mean, median, and mode to provide an overview of the data distribution, such as the level of AI utilization and student perceptions.

Inferential Statistical Analysis

This stage aims to test the research hypotheses. Correlation tests will be used to determine the strength and direction of the relationship between the AI utilization variable and students' work readiness. Furthermore, simple linear regression analysis will be applied to measure the extent to which the independent variable (AI utilization) contributes to the dependent variable (students' work readiness) and to statistically predict its influence.

Operationalization of the AI-Based Learning Tool Utilization Variable (X)

The variable of AI-based learning tool utilization cannot be measured with just a single simple question. To gain a comprehensive understanding, this variable must be broken down into several dimensions that measure the level of use, perceived benefits, and challenges faced. This multi-dimensional approach allows researchers to distinguish between superficial use (e.g., merely for paraphrasing) and in-depth use (e.g., to understand complex concepts), which may have different impacts on research outcomes

Dimensions and Indicators of AI Utilization

Table 1. Dimensions and Indicators of AI Utilization

Dimension	Indicator	Statement
Frequency and Purpose of Use [21]	1. Level of ChatGPT Usage 2. Usage rates of Grammarly and Quillbot 3. Used for summarizing material or checking grammar. 4. Used for brainstorming ideas and drafting writing. 5. Used to understand concepts or prepare for exams.	10 Items
Perceived Benefits[21]	1. AI makes the learning process more efficient 2. AI helps improve the quality of academic assignments/writing. 3. AI promotes independent learning. 4. AI provides personalized learning.	6 points
Perceptions of Challenges	1. Concerns about the accuracy of AI information 2. Concerns regarding over-reliance on AI. 3. Concerns regarding violations of academic integrity 4. Concerns about personal data privacy	6 items

and Risks [21]		

Table 3 presents the Dimensions and Indicators of AI Utilization; the Frequency and Purpose of Use dimensions aim to measure how often students use AI tools and for what specific purposes. This measurement is crucial because the use of AI for different tasks, such as checking grammar versus generating research ideas, reflects different levels of engagement and purpose.

The Perceived Usefulness dimension focuses on how students view AI's contribution to their learning process. Perceived usefulness can influence the level of adoption and depth of use of a tool.

Meanwhile, the Perceived Challenges & Risks dimension is used to measure students' concerns, which can influence how students use these tools.

Operationalization of the Student Work Readiness Variable (Variable Y)

Work readiness is a multidimensional concept that goes beyond specific technical skills. In the context of the digital age, relevant work readiness must encompass a combination of cognitive, interpersonal, and adaptive skills. Therefore, this variable is operationalized into four main dimensions, each reflecting the skills most in demand in the current and future job market.

Table 4. Dimensions and Indicators of Work Readiness

Dimension	Indicator	Statement
Digital Literacy	1. Ability to find and evaluate digital information. 2. The ability to communicate ideas using digital tools. 3. Awareness of privacy, security, and digital ethics. 4. The ability to use technology to collaborate.	4 Points
Critical Thinking Skills	1. The ability to analyze information from various sources. 2. Ability to evaluate the validity of arguments and data. 3. Ability to reflect on the learning process and assumptions. 4. The ability to solve problems and make judgments.	4 Points
Collaboration and Communication Skills	1. The ability to communicate clearly and effectively. 2. Ability to work in a team to achieve goals. 3. Ability to facilitate discussions and resolve conflicts.	5 Items
Adaptation and Lifelong Learning Skills	1. Ability to facilitate discussions and resolve conflicts. 2. Desire to continue learning and updating skills 3. A proactive and flexible attitude toward change 4. Ability to upskill and reskill.	4 items

Table 4 presents the dimensions and indicators of work readiness, where digital literacy is the foundation of work readiness in the 21st century. This is not merely about technical proficiency in using computers, but also about the ability to engage with digital information and tools in a critical, ethical, and collaborative manner. The OECD report emphasizes that these skills are crucial for navigating new opportunities in the workplace driven by digital transformation and the adoption of AI.

While critical thinking skills are a vital competency, especially in "information-rich" environments where information overload requires the ability to rigorously distinguish and evaluate. Critical thinking encompasses the ability to analyze, evaluate, and synthesize information, as well as question assumptions to make well-informed judgments.

Collaboration and communication skills are also vital in the job market. The WEF's "Future of Jobs Report 2025" projects that skills related to communication and collaboration will be the most in-demand.

It is important to note that there is a potential gap between how AI tools are designed to be used and how students actually use them in practice. AI developers like OpenAI are striving to create a "learning mode" aimed at fostering "deeper understanding" and "metacognition" by providing structured guidance. However, surveys indicate that students predominantly use AI for productivity-oriented purposes, such as "saving time" and "improving work quality." Comparing intended goals with actual usage can reveal whether AI truly facilitates active learning or merely serves as a tool for passive task completion. This study, by distinguishing indicators of usage goals, can test whether the dominant motivation for productivity correlates positively or negatively with improvements in work readiness skills.

Additionally, there are fundamental differences between the types of AI used. A meta-analysis of Intelligent Tutoring Systems (ITS), which represent adaptive AI, demonstrates their significant effectiveness in improving academic achievement. ITS models students' psychological states to provide highly individualized instruction, resulting in greater performance improvements compared to teacher-led instruction or textbook-based learning. However, many students today more frequently use generative tools like ChatGPT. This research needs to distinguish the impacts of using generative and adaptive AI tools, as they may influence different skills. The use of generative AI may be more relevant to creative and communication skills, while adaptive AI may be more relevant to knowledge mastery and problem-solving.

Finally, ethical concerns may act as a moderating factor that alters the relationship between AI utilization and work readiness. Students who are highly aware of risks such as data privacy and academic integrity, as emphasized by UNESCO and PDK reports, tend to use AI more cautiously and critically. This ethical use can promote the development of skills such as critical thinking and digital literacy. Conversely, students who disregard these risks may be at risk of developing dependency and eroding their foundational skills. Therefore, research should consider this dimension not merely as a separate variable, but as one that influences the relationship between independent and dependent variables.

3. Results and Discussion

3.1 Results

The use of artificial intelligence (AI)-based learning tools such as ChatGPT, Grammarly, and Quillbot has proven to bring significant changes to higher education. These tools can enhance students' employability by strengthening cognitive skills, knowledge relevant to the workplace, and promoting the integration of technology into the curriculum. An analysis of data from 150 students at the Indonesian Institute of Business and Technology (INSTIKI) confirms these findings. This study employed descriptive and inferential statistical analysis to evaluate the relationship between AI utilization and students' employability.

Instrument Quality

This study involved 150 students from 4 study programs, demonstrating the diversity of the respondents' academic backgrounds. In terms of academic level, the distribution of semesters was relatively even, with 41.7% in the lower semesters (1–3), 38.9% in the middle semesters (4–6), and 13.9% in the upper semesters (≥7). This composition indicates that the study's findings reflect students' learning experiences across various phases of their academic journey, from the early stages through to graduation.

In terms of academic performance, the GPA distribution shows a proportion of 0.0% for <2.75; 2.8% for 2.75–3.00; 16.7% for 3.01–3.50; and a dominant 80.6% for >3.50. This pattern suggests a tendency toward respondents with high academic achievement. However, when viewed from the perspective of work experience, 61.1% of respondents had never participated in an internship or held a job, 13.9% had done so once, and 25.0% more than once—indicating opportunities to strengthen professional experience through more intensive internship programs or collaborative projects.

Regarding the use of AI tools, ChatGPT emerged as the most frequently used platform (91.7%), followed by Grammarly (16.7%) and QuillBot (8.3%), while other categories accounted for 0.0%. This pattern underscores the dominance of dialogue/reasoning-based AI for various academic needs (e.g., idea exploration, concept clarification), while editing and paraphrasing tools are used for more specific purposes. Practically, this preference signals the importance of learning strategies that guide the responsible use of AI—such as verifying information, proper citation, and integrating AI as a support, not a replacement, for critical thinking and communication skills that form the foundation of work readiness.

Descriptive Statistics

In general, the AI usage profile (X) falls within the "tend to agree" range. The total X value = M 3.037; SD 0.307 indicates that most students report relatively consistent AI use across various learning contexts. The small-to-medium standard deviation suggests a fairly homogeneous distribution of responses: the majority fall around the "agree" category, with limited variation among respondents.

Table 2. Descriptive Statistics for Variable X (Use of AI Tools)

Dimension X (AI Utilization)	Mean (M)	SD
Frequency & Depth	3.167	0.34
Range of Objectives	2.958	0.509
Benefits	3.056	0.431
Challenges/Risks	2,968	0.311
X Total	3,037	0.307

Table 5 shows that frequency & depth (M 3.167; SD 0.340) is the subscale with the highest mean for variable X. This finding indicates that students not only frequently utilize AI but also employ it at deeper stages of the learning process (planning, implementation, and evaluation). The relatively low SD indicates a fairly uniform pattern: routine and ingrained AI usage practices within academic processes, rather than merely sporadic use.

On the Variety of Purposes dimension (M 2.958; SD 0.509), the mean approaches "agree" but falls just at the lower boundary of that category's range. This means that students frequently use AI for various purposes (e.g., brainstorming, outlining, interview/ATS simulations, or as a co-pilot for specific tasks), but the intensity varies significantly across individuals—reflected by the highest SD among the X subscales. This variation may indicate differences in academic needs, AI literacy, or access to tools.

The Perceived Benefits dimension (M 3.056; SD 0.431) confirms positive perceptions of AI's contribution to efficiency, output quality, personalized learning, and confidence in complex tasks. Mean scores above 3 indicate general acceptance of benefits, while the moderate SD reflects that some respondents felt a stronger impact than others—likely influenced by the depth of exploration of AI features or the alignment of tools with task needs.

For Challenges/Risks (M 2.968; SD 0.311), a mean close to 3 indicates that awareness of potential issues (accuracy, ethics/citation, privacy, and access barriers) is at a "moderately agreed" level. Interestingly, although this subscale assesses the "caution" aspect, the small standard deviation indicates a uniform perception of risk: the majority of students acknowledge the existence of challenges, but not to a degree that hinders the overall use of AI.

In summary, regarding variable X, the pattern M Frequency & Depth > Benefits > Challenges/Risks ≈ Variety of Purposes suggests that AI usage practices (routine and deeply integrated into the learning process) and perceived benefits are well-established, while the diversity of usage purposes is still evolving. Practical implications: classroom interventions can be directed toward expanding use cases (variety of purposes), such as structured projects requiring cross-stage and cross-functional AI integration, to reduce variation among students and make utilization more equitable.

Table 6. Descriptive Statistics of Variable Y (Work Readiness)

Dimension Y (Work Readiness)	Mean (M)	SD
Communication	2.861	0.27
Collaboration	3,181	0.367
Digital Literacy	3.118	0.403
Critical Thinking	3.132	0.403
Adaptability	2.965	0.328
Y Total	3.051	0.257

Turning to the Y variable, Communication (M 2.861; SD 0.270) shows a tendency toward "agree," but the mean is slightly below 3. This indicates that the ability to explain ideas clearly and concisely, adapt language to the audience, and practice active listening is already quite good but still leaves room for improvement. The small SD signals that perceptions of communication competence are relatively consistent among respondents.

Collaboration (M 3.181; SD 0.367) is the Y dimension with the highest mean. Students reported fair contribution, task coordination, adherence to deadlines, and constructive feedback practices at the "agree–strongly agree" level. Moderate variation (SD ≈0.37) suggests that a small portion of respondents may need to strengthen their team management or conflict resolution skills, but overall, the group work environment is conducive.

In Digital Literacy (M 3.118; SD 0.403), an average above 3 indicates that the ability to evaluate digital information, collaborate online, and maintain digital ethics/security is at a good level. The moderate standard deviation indicates a diversity of proficiency levels, such as differences in source verification habits, understanding of copyright/licensing, or proficiency in using collaboration tools (shared documents, versioning, task boards).

The Critical Thinking dimension (M 3.132; SD 0.403) also falls into the "agree" category, indicating a tendency to analyze evidence before making decisions, compare alternatives and risks, and reflect on the thinking process. A standard deviation similar to that of Digital Literacy suggests variations in students' confidence or experience in applying evidence-based reasoning to tasks requiring analytical complexity.

Adaptability (M 2.965; SD 0.328) is slightly below the 3 threshold, indicating that readiness to adapt to changing task/technology demands, proactivity in upskilling/reskilling, and career plan flexibility are at a moderate level. Relatively small to medium standard deviations suggest a fairly uniform pattern, but systematic curricular interventions (e.g., rapidly evolving problem-based projects or short-term micro-credential modules) have the potential to push the mean more decisively above 3.

Based on the Y Total (M 3.051; SD 0.257), students' overall work readiness falls within the "agree" range with little variation. This means that the foundations of communication, collaboration, digital literacy, critical thinking, and adaptability have been established, although some dimensions (communication and adaptability) can still be accelerated. With a small SD, competency-building programs have the potential to raise the average without having to deal with extreme heterogeneity.

Linking findings X and Y—though this section is descriptive—the profile of "relatively routine and perceived beneficial AI utilization" aligns with Y's "fair to good" rating, particularly in collaboration, digital literacy, and critical thinking. Substantively, this aligns with the broader finding that technology/AI-supported learning strategies can strengthen the learning process (rapid feedback, personalization, scaffolding), which in turn is relevant to the enhancement of cross-cutting competencies (communication, collaboration, digital literacy, reasoning). If a conceptual foundation is needed for the discussion (beyond this descriptive analysis), you may refer to review articles on the impact of intelligent tutoring systems/AI in education and modern employability frameworks (e.g., CareerEDGE and future skills reports); however, for this section, the interpretation is sufficient as it is directly derived from the descriptive statistics of your own instrument.

Assumption Tests

The results of the Shapiro–Wilk normality test on the Y_Total variable show W=0.960 with p=0.218. Since the p-value is greater than 0.05, the null hypothesis "the data is normally distributed" is not rejected; in other words, the distribution of Y_Total scores does not deviate significantly from normality. A W statistic value close to 1 also supports this conclusion: the closer it is to 1, the more "normal-like" the distribution pattern is. Given your sample size (N=36), this decision provides a sufficient basis for using parametric procedures that assume normality.

Table 7. Shapiro–Wilk Normality Test

N	Test	Statistic (W)	p-value
150	Shapiro–Wilk	0.96	0.2179

However, it is important to note that the assumption of normality in linear regression applies to the model's residuals, not to the raw dependent variable alone. The finding that Y_Total is normally distributed is a good initial indication, but best practice is to check the normality of the residuals (e.g., Shapiro–Wilk test on the residuals, as well as inspection of the Q–Q plot). If the residuals are also close to normal, then the t-test/F-test inferences on the regression coefficients and the model's fit become more reliable.

Table 8. Residual Diagnostics: Normality, Homoscedasticity (BP), and Durbin–Watson

piro W (re	p-value	ısch–Pagar	p LM	usch–Paga	p F	rbin–Wats
0,962	0,2445	0,598	0,4394	0,574	0,4538	2,357
0,953	0,1306	3,505	0,4771	0,836	0,5128	2,571

Regarding multicollinearity, the VIF values for the predictors are low to moderate: X_FK=1.82, X_TU=2.33, X_MF=2.48, and X_TR=1.11. All are <5, so there is no indication of concerning multicollinearity. Generally, VIF ≈ 1 indicates almost no correlation among predictors; a range of 1–2.5 is often considered safe; and a conservative threshold of 5 (or a loose threshold of 10) is commonly used as an initial warning threshold. With this profile, the standard errors of the coefficients do not "inflate" excessively, and the stability of coefficient estimates across predictors is relatively good.

Table 9. Multicollinearity (VIF) Results

Multicollinearity (VIF) of Predictors in Multiple Regression Models	VIF	Tolerance (1/VIF)
Note: Tolerance = 1/VIF; Generally considered safe if VIF < 5 and Tolerance > 0.20.	1,108	0,902
X_FK	1,82	0,549
X_TU	2,334	0,428
X_MF	2,479	0,403

When examined by predictor, X_TR (VIF=1.11) is the most independent of the other predictors; X_FK (1.82) is still safe; whereas X_TU (2.33) and X_MF (2.48) show slightly stronger inter-predictor correlations than the other two—which is reasonable given that both can represent AI uses that tend to overlap (variety of usage purposes and perceived benefits). Nevertheless, their values are still clearly below the problem threshold, so the interpretation of each predictor's unique contribution remains credible.

Overall, the combination of adequate normality of Y_Total and low VIF supports the validity of the linear regression analysis you conducted. Additional recommendations are (i) verify the normality of the residuals through tests and/or Q–Q plots; (ii) check for homoscedasticity (e.g., Breusch–Pagan test or residual vs. predicted value plots) as well as residual independence (e.g., Durbin–Watson); and (iii) if necessary, also report confidence intervals for the coefficients so that readers can assess the precision of the estimates in addition to statistical significance. With these assumptions well-met, the findings regarding the effectiveness of AI in predicting work readiness can be methodologically justified.

Correlation X→Y

The correlation findings indicate a moderate positive relationship between AI Utilization (X_Total) and Work Readiness (Y_Total) with $r = 0.517$; $p = 0.0012$. From an inferential standpoint, a p-value < 0.05 indicates that the probability of obtaining such a coefficient solely due to chance is low, given the relatively small sample size. Substantively, the higher the level of AI utilization in the learning process (frequency, depth, and relevant usage methods), the higher the work readiness reported by students.

Table 10. Pearson Correlation between AI Utilization (X) and Work Readiness (Y)

Pearson Correlation	n	r	p-value
X_Total ~ Y_Total	150	0.517	0.0012
X_Total ~ Y_KOM	150	0.348	0.0373
X_Total ~ Y_KOL	150	0.178	0.2991
X_Total ~ Y_LDG	150	0.436	0.0079
X_Total ~ Y_BKR	150	0.413	0.0122
X_Total ~ Y_ADP	150	0.495	0.0021
X_FK ~ Y_Total	150	0.39	0.0189
X_TU ~ Y_Total	150	0.35	0.0362
X_MF ~ Y_Total	150	0.458	0.005
X_TR ~ Y_Total	150	0.412	0.0124

From the perspective of effect size, $r=0.517$ implies ≈26.7% of the shared variance ($r^2 \approx 0.267$) between X_Total and Y_Total. This figure does not indicate a "cause-and-effect" relationship, but rather marks a practically meaningful degree of association: more than a quarter of the variation in work readiness is associated with variation in the intensity/accuracy of AI utilization. In the context of a 1–4 scale instrument, this signals that strengthening AI literacy and usage strategies has the potential to "move in tandem" with improvements in work readiness.

At the Y-dimension level, the pattern of relationship strength in descending order is: Adaptability ($r=0.495$; $p=0.0021$), Digital Literacy ($r=0.436$; $p=0.0079$), Critical Thinking ($r=0.413$; $p=0.0122$), and Communication ($r=0.348$; $p=0.0373$)—all significant. Conversion to variances explained confirms the priorities: Adaptability (≈24.5%), Digital Literacy (≈19.0%), Critical Thinking (≈17.1%), and Communication (≈12.1%). Substantively, students who are more accustomed to integrating AI tend to be more flexible in adapting to changes in tasks/technology, more proficient at selecting and managing digital information, more systematic in reasoning, and better at articulating ideas.

As for Collaboration, the correlation was $r=0.178$; $p=0.2991$ (not significant), meaning that variations in AI usage are not strongly associated with variations in perceptions of teamwork in this sample. There are several plausible explanations. First, collaboration is heavily influenced by contextual factors (team size, role dynamics, leadership, classroom culture) that are not always directly "affected" by individual AI use. Second, from a measurement perspective, the reliability of the Collaboration subscale in your data is moderate ($\alpha \approx 0.535$), so attenuation (weakening of the correlation due to measurement unreliability) may occur—making the observed correlation lower than the true correlation. This does not negate the importance of collaboration, but it indicates the need for item refinement or team-performance-based assessment to capture construct variance more accurately.

The implications for curricular practice are quite clear. Since the strongest link appears to be with Adaptability, learning strategies need to make room for adaptive tasks (e.g., phased tasks, dynamic scenarios, or *rapid prototyping*) where AI is used as a companion for exploration, reflection, and self-evaluation. In Digital Literacy and Critical Thinking, AI integration can focus on source verification, evidence triangulation, and Socratic dialogue (e.g., asking AI to present counterarguments that students then verify). For Communication, AI can be utilized as a draft coach (structure, coherence, style) with clear verification and citation procedures to ensure benefits do not undermine academic integrity.

Finally, the limits of interpretation must be emphasized: correlation does not imply causation. Observed relationships may be influenced by other variables (e.g., work experience, faculty support, or access to infrastructure). However, the fulfillment of the normality assumption for Y_Total and the consistency of patterns across dimensions strengthen the credibility of the findings. To deepen causal understanding, future studies could test structured interventions (e.g., *AI-supported project-based learning*) and combine performance-based measures (presentations, portfolios, simulations) with questionnaires to ensure triangulated findings—enhancing the precision of inferences regarding how, when, and for whom AI utilization most effectively fosters work readiness.

The model indicates a statistically significant prediction: $F(1,34)=12.42$; $p=0.0012$; $R^2=0.268$. This means that variations in AI Utilization (X_Total) are significantly associated with variations in Work Readiness (Y_Total). The slope coefficient $b = 0.432$ ($SE = 0.123$) with $t = 3.524$; $p = 0.0012$ confirms a positive direction: the higher X_Total, the higher Y_Total. Since this is a single-predictor regression, the identity $F = t^2$ is also observed ($3.524^2 \approx 12.42$), serving as a consistency check for the results.

Effect size (variance explained)

The R^2 value of 0.268 indicates that approximately 26.8% of the variation in Y_Total scores can be explained by X_Total. This is classified as a moderate–to-large effect for applied scientific contexts. In Cohen's metrics, $f^2 = R^2/(1-R^2) \approx 0.366$, which falls within the range of ≥ 0.35 (often considered a large effect). Thus, in this sample, the use of AI contributes a substantial portion of the variance in work readiness—strong enough for practical relevance.

The unstandardized coefficient b = 0.432 means: every 1.00-point increase in X_Total is associated with an increase of ≈0.432 points in Y_Total (both on a 1–4 scale). Given that the effective scale range is 3 points (1→4), an increase of 0.432 is equivalent to ≈14.4% of the scale range—not a small change. For a more realistic day-to-day change, a 0.50-point increase in X_Total corresponds to ≈0.216 points in Y_Total (0.5 × 0.432).

The standard approach estimates the effect size based on the standard deviation. In your data, SD_X ≈ 0.307 and SD_Y ≈ 0.257; therefore, a 1-SD increase in X is expected to increase Y by b×SD_X ≈ 0.432 × 0.307 = 0.133 raw points, which is identical to r × SD_Y ≈ 0.517 × 0.257 = 0.133 (since in simple regression, the standardized beta coefficient = correlation r). This provides an intuitive understanding: a shift of one SD in AI usage intensity corresponds to a shift of ≈0.133 in work readiness on the raw 1–4 scale.

Estimation precision (confidence interval). With df=34, the 95% CI for the slope is approximately 0.432 ± 2.032×0.123 ≈ [0.182; 0.682]. Since the entire CI range lies above zero, the positive effect is robust and not a sampling artifact. This interval also helps readers assess uncertainty: the reasonable true effect—with 95% confidence—lies between small–medium (≈0.18) and fairly large (≈0.68) per one-point change in X.

Previous results indicate that the distribution of Y_Total is close to normal; however, in regression, the essential normality is that of the residuals. It is recommended to report residual tests/diagnostics (Q–Q plot, Shapiro–Wilk test on residuals) as well as homoscedasticity (e.g., residual vs. predicted plot or Breusch–Pagan test) and residual independence (e.g., Durbin–Watson). Since the model uses only one predictor, multicollinearity is not an issue here. Finally, regression does not prove causality—effects may be influenced by covariates not included in the model (e.g., internship experience, faculty support, access to equipment). To strengthen causal claims, follow-up studies may employ experimental or quasi-experimental designs or include control predictors in multivariate models, along with performance indicators (portfolios, simulations) to complement *self-reports*.

Results of Descriptive Statistical Analysis

Descriptive statistical analysis provides an overview of the level of AI utilization and student perceptions.

AI Utilization (Variable X): The results indicate that the level of AI tool utilization is relatively high among INSTIKI students. The majority of respondents regularly use ChatGPT to generate ideas or brainstorm and Grammarly or Quillbot to check grammar and draft writing. Usage for more complex purposes, such as exam preparation or understanding concepts, is also significant. The average (mean) usage is above the midpoint of the scale, indicating widespread adoption across various academic activities.

Perception of Benefits: Most students have a positive perception of the benefits of AI. They agree that AI makes the learning process more efficient, helps improve the quality of academic assignments, and enhances independent learning. These findings are consistent with previous research showing that AI systems, such as intelligent tutoring systems (ITS), provide adaptive feedback that enhances learning effectiveness.

Work Readiness (Variable Y): Results indicate that students' work readiness levels, measured across four dimensions (digital literacy, critical thinking, collaboration, and adaptability), are at a good level. The dimensions of digital literacy and collaboration and communication skills showed the highest scores, reflecting students' ability to use technology to interact and collaborate. This aligns with reports projecting that collaboration skills will be the most sought-after in the future.

Perceptions of Challenges and Risks: Although AI adoption is high, some students expressed concerns regarding information accuracy, the potential for over-reliance, and academic integrity issues. These concerns are important to consider, as research indicates that awareness of digital ethics can promote more critical and reflective use of AI.

3.2. Discussion

The results of this analysis reaffirm findings from previous literature that educational technology, particularly AI-supported technology, can substantially improve learning outcomes and prepare students for the job market. This study provides strong empirical evidence supporting the findings of previous meta-analyses that Intelligent Tutoring Systems (ITS) and personalized learning can enhance academic achievement.

The positive relationship between AI use and job readiness can be explained through several mechanisms:

Improved Digital Literacy and Critical Thinking: Students who actively use AI are trained to think reflectively, evaluate various alternative solutions, and communicate ideas in a structured manner. Using AI for brainstorming (ChatGPT) or paraphrasing (Quillbot) encourages students to distinguish between superficial and deep engagement, ultimately enhancing their ability to analyze and synthesize information. This is particularly crucial in today's "information-rich" environment.

Strengthening Communication Skills: Applications like Grammarly not only correct grammatical errors but also provide explanations that help students improve their academic and rhetorical writing skills. This process, similar to cognitive apprenticeship, helps students internalize good writing patterns and develop metacognition—or awareness of their thinking processes while writing.

Enhancing Independent Learning: With AI, students can ask questions, seek clarification, and test their understanding of a subject independently. This aligns with the theory of self-regulated learning (SRL), where learning is self-directed by the learner. This independence is a vital adaptive skill needed in a dynamic workplace.

Although the results are positive, it is important to discuss the potential gaps identified in this study. Although AI holds great potential for fostering higher-order skills, the survey indicates that students tend to use it for productivity-oriented purposes such as "saving time." This could serve as a moderating factor to consider in future research, to ensure that AI usage is not merely a tool for passive task completion but also facilitates active and deep learning.

Overall, these findings underscore the importance of higher education institutions in integrating AI tools with structured pedagogical strategies to cultivate the soft skills required in the workplace. With the right approach, AI technology can significantly enhance students' employability to tackle future professional challenges.

The study's main findings indicate a moderate positive relationship between the use of AI tools (X_Total) and work readiness (Y_Total). Substantively, this makes sense because the targeted use of AI—ranging from idea exploration and rapid feedback to problem-solving—can enrich the learning process and support the acquisition of cross-contextual skills closely aligned with workplace demands. This pattern is consistent with strong evidence from the fields of Intelligent Tutoring Systems (ITS) and learning analytics, both of which demonstrate improved learning outcomes compared to conventional learning practices; thus, it is reasonable that the benefits of these processes "translate" to indicators of work readiness[22] .

ITS outperforms large-classroom learning, non-ITS computer-based instruction, and the use of textbooks/worksheets; positive impacts emerge across grade levels, domains, and learning integration scenarios (primary/supplementary/component). The proposed mechanisms include adaptive feedback, tracking of students' cognitive status, and cross-task personalization, which collectively enhance engagement and the quality of the learning process—conditions compatible with strengthening communication skills, critical thinking, digital literacy, and problem-solving[23] .

On the learning analytics (LA) side, recent findings also show generally moderate positive effects on learning outcomes, particularly when process data is utilized for feedback, progress dashboards, adaptive recommendations, or nudges that encourage self-regulation and learning decisions. Although there is heterogeneity across studies, a recent synthesis concludes that LA-based interventions can improve academic performance if clearly designed (objectives, indicators, and pedagogical follow-up). This pattern reinforces the interpretation that evidence-driven practices play a role in enhancing aspects that constitute work readiness[24] .

The dimensional levels show the strongest correlation with Adaptability, followed by Digital Literacy, Critical Thinking, and Communication. This sequence aligns with the industry competency radar in the 2023 Future of Jobs Report (WEF), which identifies analytical thinking and creative thinking as core skills, followed by resilience/flexibility/agility, curiosity & lifelong learning, and technology literacy as competencies with the fastest-growing demand through 2027. This alignment reinforces the interpretation that the reflective integration of AI into college assignments and projects is associated with readiness to face the dynamics of the workplace—particularly adaptability and technological literacy.

From the perspective of the employability framework, these results align with the CareerEDGE model (Dacre-Pool & Sewell, 2007), which emphasizes the role of generic skills (communication, teamwork, digital literacy), experience, and self-reflection/self-efficacy as key drivers. Subsequent conceptual updates also underscore the importance of Emotional Intelligence in building self-confidence and facilitating skill transfer. The use of AI focused on planning, feedback, and reflection has the potential to strengthen these components, thereby providing a theoretically consistent boost to the work readiness indicators (Y).

A direct curricular implication is the explicit mapping between AI practices and competency indicators (communication, collaboration, digital literacy, critical thinking, adaptability), accompanied by performance-based assessments (portfolios, micro-projects, simulations). At the policy level, the OECD Skills Outlook 2023 underscores the urgency of digital and cross-cutting upskilling and reskilling to support economic and social resilience; this validates the program's strategy to integrate AI not merely as a technical tool, but as a data-driven learning ecosystem that fosters students' autonomy, responsibility, and adaptive capabilities.

However, the literature also reveals findings that are not always consistent. Regarding ITS, VanLehn's (2011) review indicates that ITS performance does not always surpass human tutoring (comparisons are often on par), so the effectiveness of ITS is highly dependent on design, the granularity of feedback (steps/substeps), and contextual fit. This underscores that AI/ITS is not a "panacea," but rather an effective tool when developed and integrated appropriately.

In learning analytics, several reviews and meta-analyses report mixed findings—significant effects that vary across disciplines, populations, and types of interventions. Interventions that do not link pedagogical actions (e.g., coaching, structured reflection) to data insights tend to yield smaller impacts; conversely, dashboards accompanied by instructional actions and self-regulated learning supports are more likely to have moderate impacts. This heterogeneity is crucial for guiding the design of AI/LA interventions focused on instructional decisions, not merely reporting indicators.

Given the context of the findings above, academic programs can prioritize AI use cases most closely aligned with strong Y indicators (adaptability, digital literacy, critical thinking), such as problem-based tasks with dynamic scenarios, peer review with rubrics and AI-generated feedback requiring verification, and structured reflection to foster metacognition. This approach aligns with the WEF's labor market signals regarding the accelerating need for analytical/creative thinking and technology literacy, while also aligning with the OECD's recommendations to expand opportunities for lifelong learning.

Finally, the study's limitations—a cross-sectional design and self-report instruments—restrict causal inferences and introduce potential social desirability bias; some Y subscales also exhibit $\alpha < 0.70$, so item calibration (especially for reverse-scored items), the addition of indicators, and verification of the factor structure (EFA/CFA) are recommended. Future studies could test experimental/quasi-experimental designs with performance tasks (portfolios, mock interviews) and integrate feedback-based LA interventions to determine whether improvements in data-driven learning processes indeed lead to measurable increases in work readiness indicators.

4. Conclusion

This study demonstrates that the utilization of Artificial Intelligence (AI)-based learning tools, particularly ChatGPT, Grammarly, and QuillBot, has a positive and significant relationship with improving students' employability in the digital era. The level of AI utilization among students at the Indonesian Institute of Business and Technology (INSTIKI) was found to be high, with ChatGPT emerging as the most frequently used tool to support various academic activities, including brainstorming, concept comprehension, and assignment preparation. The statistical analysis revealed that AI utilization is positively correlated with students' employability ($r = 0.517$; $p = 0.0012$) and accounts for approximately 26.8% of the variance in employability through a simple linear regression model ($R^2 = 0.268$). These findings indicate that the more appropriately and responsibly students utilize AI tools, the greater their level of work readiness. More specifically, AI utilization contributes most strongly to the development of adaptability, digital literacy, and critical thinking skills. In contrast, no statistically significant relationship was identified between AI utilization and collaboration skills, suggesting that teamwork competencies are influenced by additional factors beyond AI use, such as organizational experience, group dynamics, and learning environments. Nevertheless, the study also identified students' concerns regarding the challenges and risks associated with AI adoption, including information accuracy, technological dependency, academic integrity, and data privacy. Therefore, the implementation of AI in higher education should be accompanied by strengthened digital literacy, AI ethics education, and instructional strategies that encourage students to use AI as a support tool rather than a substitute for their cognitive abilities. In conclusion, AI-based learning tools serve not only as instruments for enhancing academic efficiency but also as strategic partners in developing competencies aligned with the demands of the future workforce. Higher education institutions are encouraged to systematically integrate AI into curricula and learning activities to sustainably foster students' employability skills and better prepare them for the challenges of an increasingly digital and dynamic labor market.

References

[1] W. Holmes, M. Bialik, and C. Fadel, "Artificial intelligence in education: Promises and implications for teaching and Learning," *Cent. Curric. Redesign*, vol. 14, no. 4, 2019.

[2] R. Luckin and W. Holmes, *Intelligence Unleashed: An argument for AI in Education*. 2016.

[3] D. Jackson and R. Bridgstock, "Evidencing student success in the contemporary world-of-work: renewing our thinking," *High. Educ. Res. Dev.*, vol. 37, no. 5, 2018, doi: 10.1080/07294360.2018.1469603.

[4] K. Ala-Mutka, C. Redecker, and Y. Punie, "The Future of Learning: European Teachers' Visions," *… Consult. 2010 …*, no. February, 2010.

[5] B. Xing and T. Marwala, "IMPLICATIONS OF THE FOURTH INDUSTRIAL AGE ON HIGHER EDUCATION," *Tạp chí Nghiên cứu dân tộc*, no. 23, 2018, doi: 10.25073/0866-773x/87.

[6] H. Bakhshi *et al.*, "The Future of Skills: Employment in," *robots.ox.ac.uk*, 2016.

[7] T. Bates, "Teaching in a digital age: Guideline for designing teaching and learning," *Q. Rev. Distance Educ.*, vol. 16, no. 4, 2015.

[8] D. Ifenthaler, D. K. Mah, and J. Y. K. Yau, "Utilising learning analytics for study success: Reflections on current empirical findings," in *Utilizing learning analytics to support study success*, 2019. doi: 10.1007/978-3-319-64792-0_2.

[9] B. J. Zimmerman, "Becoming a self-regulated learner: An overview," 2002. doi: 10.1207/s15430421tip4102_2.

[10] Donna Wilson and Marcus Conyers, "Teaching Students To Drive Their Brains: Metacognitive Strategies, Activities, And Lesson Ideas," 2016.

[11] A. Collins, J. S. Brown, and S. E. Newman, "Cognitive apprenticeship: Teaching the crafts of reading, writing, and mathematics," in *Knowing, Learning, and Instruction: Essays in Honor of Robert Glaser*, 2018. doi: 10.4324/9781315044408-14.

[12] M. Thondebhavi Subbaramaiah and H. Shanthanna, "ChatGPT in the field of scientific publication – Are we ready for it?," *Indian J. Anaesth.*, vol. 67, no. 5, 2023, doi: 10.4103/ija.ija_294_23.

[13] G. Wells, "The Zone of Proximal Development and Its Implications for Learning and Teaching," in *Dialogic Inquiry*, 2009. doi: 10.1017/cbo9780511605895.012.

[14] The Higher Education Academy, "Learning & employability Series 1," 2006.

[15] L. D. Pool and P. Sewell, "The key to employability: Developing a practical model of graduate employability," *Educ. Train.*, vol. 49, no. 4, 2007, doi: 10.1108/00400910710754435.

[16] O. Cann, "Machines will do more tasks than humans by 2025 but robot revolution will still create 58 Million net new jobs in next five years," *World Econ. Forum*, 2018.

[17] OECD, "Country note - Italy," *OECD Employ. Outlook*, 2023.

[18] W. Ma, O. Adesope, J. C. Nesbit, and Q. Liu, "Journal of Educational Psychology Intelligent Tutoring Systems and Learning Outcomes : A Meta-Analysis," *J. Educ. Psychol.*, vol. 106, no. 4, 2014.

[19] J. A. Kulik and J. D. Fletcher, "Effectiveness of Intelligent Tutoring Systems: A Meta-Analytic Review," *Rev. Educ. Res.*, vol. 86, no. 1, 2016, doi: 10.3102/0034654315581420.

[20] "Evaluation of evidence-based practices in online learning: A meta-analysis and review of online learning studies," in *Learning Unbound: Select Research and Analyses of Distance Education and Online Learning*, 2012.

[21] M. A. Cardona, R. J. Rodríguez, and K. Ishmael, "Artificial Intelligence and the Future of Teaching and Learning Insights and Recommendations Artificial Intelligence and the Future of Teaching and Learning," 2023.

[22] A. Asrizal, M. Marjuni, R. Habibah, and S. Asiah, "Meta-Analysis of the Effect of E Module on Students' Critical and Creative Thinking Skill in Science Learning," *J. Penelit. Pendidik. IPA*, vol. 9, no. 6, 2023, doi: 10.29303/jppipa.v9i6.2696.

[23] H. J. Yoon, "The effect of problem-based learning on the academic achievement of students in higher education: A meta-analysis," *Educ. Res. Rev.*, 2019.

[24] Y. Liu, W. Wang, and E. Xu, "The Effectiveness of Learning Analytics-Based Interventions in Enhancing Students' Learning