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ENHANCING EMPLOYABILITY OUTCOMES THROUGH AI TOOLS: A SEM-SPLS APPROACH WITH TAM AND SOFT SKILLS MEDIATION

Ahmed Alabri [(a)] *Boumedyen Shannaq* [(b)1]

[(a)]*Finance and Administrative Affairs & Supporting Services, University of Buraimi, Al Buraimi 512, Sultanate of Oman; E-mail: drahmed.s@uob.edu.om*
[(b)]*Management of Information Systems Department, University of Buraimi, Al Buraimi Governorate, Sultanate of Oman; E-mail: boumedyen@uob.edu.om*

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ABSTRACT

There has been increased interest in understanding how AI is enhancing people's ability to secure a good job lately, due to its rapid adoption in schools and workplaces. However, the relationships between how easy AI is to use and how valuable people think it is to its actual usefulness for getting a job are little studied. It examines the relationship between the usability of AI tools, their practical value, and their impact on employability, where soft skills act as a bridge between them. It studies the relationship between factors using Structural Equation Modeling and Partial Least Squares (SEM-PLS), exploring data from 429 users of learning environments. The study highlights significant relationships between constructs that are statistically significant, utilizing the Technology Acceptance Model (TAM). The findings show that the perceived usefulness of AI tools explains nearly a fifth of the changes in soft skills (18.1%) and close to a fifth of the improvements in employability outcomes (19%). In the same way, how easy a technology is to use (AI_EU_TAM) is essential for developing soft skills (β = 0.374, p = 0.000) and for getting a job (β = 0.246, p = 0.000). Having strong soft skills is very important for employment since it affects employability by 0.504 points (p = 0.000). Mediation confirms that soft skills help explain 56.1% of the relationship between AI_PU_TAM and EM and 76.8% of the relationship between AI_EU_TAM and EM. The results offer a unique perspective, demonstrating that the use of AI tools facilitates the development of new skills that support employability, which can inform future studies on online education and employment preparation.

INTRODUCTION

The global employment environment is undergoing rapid developments due to digital progress, including the growth of Artificial Intelligence (AI) (Abbas Khan et al., 2025). Direct-effect AI tools, including ChatGPT, have gained significant influence in education, becoming crucial in professional training systems and human resource selection processes. Higher education and training institutions are seeking new approaches to enhance graduate employability, making AI tools an attractive solution for academic skill development and education (Asim et al., 2024; Khatri, Arora, & Khan, 2024; Kumar et al., 2025). SEM with PLS techniques will evaluate the changes in employability outcomes resulting from the use of direct-effect AI tools in research that assesses this relationship (Falebita & Kok, 2024). Research applies the Technology Acceptance Model (TAM) to examine users' perceptions of AI tools and introduces soft skills as an intermediary variable. According to Alzubaidi and Khalid (2025), AI improves graduate employability in transnational education by enhancing job readiness, aligning curricula with industry needs, and increasing student satisfaction, despite ongoing concerns about ethics and inclusivity. As noted by Jackson et al. (2024), career services enhance student employability through counseling, skills training, and industry engagement, while addressing evolving challenges with technology and strategic partnerships.

According to Badulescu et al. (2025), AI reshapes education and labor demands, emphasizing collaboration between education and business to develop future-ready competencies for AI-driven career success.AI tools in training and education continue to spread, while researchers have conducted minimal investigations into how these tools lead to either

[1]Corresponding author: *ORCID ID: 0000-0001-5867-3986*

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direct or indirect changes in employability outcomes. There is a critical deficiency in research regarding how better soft skills can be achieved through AI tools compared to direct AI applications for career intervention enhancement.

Public organizations' research and development in management science builds staff skills in thinking ahead, communicating, and resolving issues, helping them adjust well to any changes. Enhancing these traits leads to improved employment opportunities by ensuring that public sector innovation meets the evolving needs of the workplace (Asim & Sorooshian, 2022). With Industry 5.0, the primary goal in healthcare is to prioritize people, so healthcare workers must possess empathy and effective communication skills. Addressing such obstacles enhances a person's chances of working in modern, technology-driven healthcare settings (Asim, Z., 2022). Servant leadership fosters empathy and teamwork, enhancing citizenship behavior within organizations. They enhance employability in social work by fostering group trust and cooperation (Khatri, Sharma, Khan, & Nandini, 2024). It also helps physicians develop essential soft skills, such as decision-making and flexibility, which improve their job prospects, as it focuses on both hands-on and technology-based learning experiences in Jordan's healthcare system (Jawarneh et al., 2023).

Studies on AI tools have primarily evaluated their technical capabilities and their impact on cognitive learning abilities. Research lacks a sufficient investigation of how the development of soft skills, specifically communication, teamwork, and critical thinking, mediates the outcomes of employability (Mäkelä & Stephany, 2024). Research lacks empirical models that integrate the SEM-SPLS analytical approach with all three components of the Technology Acceptance Model (TAM), combined with soft skills and employability measurements (Alazzawi et al., 2025).

What makes this work important is that it addresses a vital omission in studies of education and the job market: the impact of artificial intelligence on the development of soft skills required for employment. Although AI is transforming education and training globally, there aren't enough studies to explain how these tools help people get jobs. By combining TAM with soft skills development, this study shifts our attention from solely technical achievements to fully considering the effects on human participants.

This research focuses on a crucial topic: how the use of AI tools affects the essential soft skills that workers require for their jobs, including teamwork, communication, and critical thinking. At present, explorations of AI mainly examine the technology's impact on the mind and not enough on how it can improve people's social and interpersonal abilities. The SEM-PLS method employed in this work enables this research to link individuals' perceptions of AI to its positive impact on skills, thereby advancing their employability.

This study explores several interrelated questions regarding the role of AI tools in workforce development: First, it examines how workers' perceived usefulness of AI (PU) influences their subsequent job market performance. Second, it investigates whether basic engagement with AI tools affects their acceptance and integration within employability training programs. Third, it evaluates the impact of using AI-driven soft skill improvement tools on the employability outcomes of employees who adopt these technologies. Finally, the research seeks to determine whether direct implementation of AI tools or a focus on soft skill enhancement via AI constitutes the most effective strategy for boosting employability.

This research aims to examine how workers perceive the usability and usefulness of AI tools in relation to their employability outcomes and to assess whether soft skills mediate the relationship between AI tool adoption and employability. By developing a conceptual SEM-SPLS model, the study will identify which AI-based strategies most effectively enhance career placement opportunities. Ultimately, the findings will generate actionable insights for policymakers, educational institutions, and hiring organizations as they design AI-driven training programs.

Researchers will find these findings very useful. This model supports upcoming investigations into AI-enabled education and jobs by providing an easy-to-use method for evaluating the broader impact of AI. Furthermore, this work guides the creation of scalable training programs, updates policies, and develops AI models that emphasize comprehensive skill sets. It is an essential way to integrate AI education into what employers require, helping people build skills that matter in the future. This study demonstrates that soft skills significantly mediate the relationship between AI usability and perceived usefulness, leading to improved employability outcomes.

The information in the paper is arranged into five critical sections for easy understanding. Section 2 provides a comprehensive review of relevant studies on the application of AI in HR, outlining what is currently known and what remains unknown. Section 3 describes the materials and methods, while Section 4 shows the Experiment and results.

LITERATURE REVIEW

The adoption of Artificial Intelligence tools by professionals has significantly altered employment outcomes, as they have impacted how workers interact with one another in the workplace. As AI is increasingly used in workplaces, it has also changed employment conditions, making it essential to understand how people interact with these systems. Studies conducted recently suggest that Perceived Usefulness (PU) and Perceived Ease of Use (EU) are significant factors that determine AI adoption and the effects on people's employability (Almeida et al., 2025; Bankins et al., 2024). Individuals who find AI tools easy to use and helpful are more likely to adapt to them, leading to improved outcomes and better job prospects.

Technology Acceptance Model (TAM)

To understand why users accept new technologies, Davis et al. (1989) introduced the Technology Acceptance Model (TAM). It links PU and EU as the fundamental variables that guide feelings about using technology. TAM, when applied to AI, can help people decide if a new technology such as ChatGPT, is simple to adopt and offers useful functions (Wang et al., 2023). Its success has been evident in various areas, including e-commerce, education, mobile banking, and robotics (Shaikh & Karjaluoto, 2015; Pillai et al., 2023). People's cultural backgrounds play a role in guiding their attitude toward using AI. For example, people's habits, shaped by their culture and ability to use computers and technology, influence their

use of conversational AI, such as ChatGPT (Kuang et al., 2023). In addition, the present study employs the Technology Acceptance Model (TAM) to investigate how Perceived Usefulness (PU) and Ease of Use (EU) impact the development of Soft Skills (SK) and their influence on Employability Outcomes (EM), particularly in culturally diverse and technologically evolving environments.

AI-TAM Perceived Usefulness (PU)

If individuals think that an AI system will make them work better and improve their chances of getting a job, it is called Perceived Usefulness (PU). According to studies, AI tools lead to user productivity, which in turn strengthens their motivation to continue using them (Bankins et al., 2024). According to Wang et al. (2023), the use of PU has led to an increase in the adoption of e-commerce and educational tools, confirming its key role in advancing the acceptance of technology. With the rise of AI in the workplace, it is essential to utilize performance management tools (PU) to ensure employees' performance aligns with digital change. Believing that using technology helps in performing well and may influence our intention to behave is known as Perceived Usefulness (PU) and is a key concept in the Technology Acceptance Model (TAM) (Davis et al., 1989; Venkatesh & Davis, 2000). It is regularly observed that PU can predict how many users will use specific systems. Studies have proven that PU influences an individual's willingness to use AI chatbots (Pillai & Sivathanu, 2020), innovative healthcare services (Liu & Tao, 2022), and voice assistants (Cai et al., 2022). With ChatGPT being integrated into customer service and healthcare, people report higher satisfaction and better service (Cascella et al., 2023; Koc et al., 2023; Rahimzadeh et al., 2023).

Because of these results, we can propose the following hypotheses:

***H_1**: The perceived usefulness (PU) of AI tools has a positive influence on Employability Outcomes (EM).*
***H_2**: The perceived usefulness (PU) of AI tools positively influences Soft Skills (SK).*

AI-TAM Ease of Use (EU)

Ease of Use (EU) refers to the amount of effort a user perceives as required to work with AI tools. A simple and user-friendly interface helps people form more positive thoughts about adoption, as they feel more confident in using the technology (Almeida et al., 2025). Using simple tools leads to better user involvement, which in turn makes tools seem worthwhile and raises the desire to use them. The EU helps determine how accessible AI tools are to everyone, regardless of their skills, and encourages workers to utilize them effectively.

According to TAM, perceived ease of use (PEOU) refers to the amount of effort a user expects to expend when using a technology (Davis et al., 1989). Numerous AI-based studies demonstrate that perceived ease of use (PEOU) plays a significant role in influencing users' decisions to adopt new technologies. For example, PEOU increased employees' intention to work with customer service AI, as per Chatterjee et al. (2021), and drove up students' use of AI robots for learning (Pillai et al., 2023). Because ChatGPT is easy to use and intuitive, more people are interested in using it and interacting for longer (Liu & Ma, 2023). They confirm that the simpler the technology is to use, the likelier people are to adopt it. Considering these studies, it is thought that people who see ChatGPT as convenient will be most likely to use it. H2. When people perceive ChatGPT as simple to use, they are more likely to proceed with its use.

Recent efforts in artificial intelligence research have highlighted that users' perceptions are crucial to the adoption of technology. PEOU is a central part of the Technology Acceptance Model (TAM), as it typically influences Perceived Usefulness (PU), particularly in tools based on artificial intelligence (AI). According to Wang et al. (2023), if an AI system is easy to navigate and use, people usually consider it helpful in attaining their goals. As found in previous large-scale studies, user-friendliness in interactions with technology enhances users' perceived usefulness of the technology. Due to its simple interface and intuitive interaction, ChatGPT helps users feel confident that it performs as intended.

Because of these results, we can propose the following hypotheses:

***H_3**: The ease of use (EU) of AI tools positively influences Employability Outcomes (EM).*
***H_4**: The ease of use (EU) of AI tools positively influences Soft Skills (SK).*

Soft Skills (SK)

IT graduates tend to be highly technologically skilled, but they need to develop their soft skills. In particular, Finnish and Italian students were troubled by the challenges in communication and teamwork, which conflicted with what employers expect, despite being strong in technical areas (Caggiano et al., 2020). The use of soft skills was positively correlated with the adoption of the flipped classroom and self-paced learning methods in Morocco. As a result of using these approaches, students develop knowledge within their subjects and also work more effectively as a team, discussing issues and solving problems (Moundy et al., 2022). Teamwork and communication skills are typically well-developed among Malaysians; however, essential soft skills such as critical thinking and adaptability are often lacking (Mitchell & Vaughan, 2022).

An international study spanning 24 nations emphasized the importance of integrating teamwork and project management into IT courses. Increasingly, companies are reluctant to invest time in retraining college graduates on fundamental soft skills, underscoring the importance of colleges revising their curricula (Sahin & Celikkan, 2020). Specific needs that arise within each industry continue to highlight where the gap lies. Many educators in Thailand lack an understanding of the requirements for IT jobs, which makes it more challenging to incorporate soft skills into such programs. Combining the efforts of universities and companies can help close the gap between research and industry (Siddoo et al., 2019).

Those in cybersecurity in Turkey are expected to be able to lead and communicate effectively, in addition to

possessing technical knowledge. For this reason, teaching soft skills should be emphasized in management study programs (Catal et al., 2023). Although AI and IoT are advanced in India, a focus on soft skills is still lacking. As a consequence, several graduates lack the skills needed for Industry 4.0 jobs, which often require individuals to be both adaptable and effective in dealing with others (Satpathy et al., 2020).

Employability Outcomes (EM)

Employability outcomes indicate whether an individual can secure and maintain a job. It examines how introducing AI enhances workers' soft skills and facilitates job placement. It helps people prepare for careers in AI, primarily for adult learners. According to the study, computer-based coaching should blend the technical abilities needed with key soft skills to adapt to the latest industry trends (Subramanian & R, 2024).

Many people around the world now recognize that soft skills are crucial for securing a job. Learning approaches that mirror the job market in Australia and the UK have shown that to succeed in their careers, students should excel in critical thinking, creativity, and innovation (Scott & Willison, 2021). Combining soft skills training with operating systems lessons results in students being more engaged in the course and better prepared for jobs, according to studies in the U.S. (Buckley, 2020) that utilize both synchronous online and face-to-face approaches. When graduating from engineering in Malaysia, students are required to possess soft skills in relationship management, self-awareness, and business acumen. Developing a wide range of skills is crucial for addressing the diverse needs of the industry (Fitriani & Ajayi, 2022). The use of technology affects how employable someone can be. Students in Italy have improved their practical skills by incorporating soft skills into hardware-software systems (Chessa et al., 2022).

In addition, SKILLS+ encourages a learning style that focuses on students, enabling them to become team leaders and develop skills in creative thinking and project reshaping (Cottafava et al., 2019). In Romania, the use of soft skills in micro-enterprises of the ICT sector has so far helped improve the situation. Education in communication, teamwork, and problem-solving permits smaller businesses to use more advanced tools in training their employees (Szilárd et al., 2018).
Based on previous studies related to Soft Skills (SK) and Employability Outcomes (EM), this work suggests that the following hypothesis is acceptable.

***H_5**: Soft Skills (SK) mediate the relationship between the perceived usefulness (PU) of AI tools and Employability Outcomes (EM).*
***H_6**: Soft Skills (SK) mediate the relationship between the ease of use (EU) of AI tools and Employability Outcomes (EM).*

Unresolved Issues and Research Gaps

Even though much is being researched on the connection between Soft Skills (SK) and Employability Outcomes (EM), some crucial gaps are yet to be filled. While soft skills matter a lot in the job market, many studies still disagree about which ones are more valued. Because the organization is not aligned, its curriculum and training programs are usually fragmented. Even so, the Technology Acceptance Model (TAM) is widely used to explain technology adoption; however, there has been limited research on its relationship with soft skills and employment. The role of usefulness and ease of use in employment is debated, as studies show that they greatly facilitate job finding, while others suggest they have little or no effect. Additionally, systematic studies on how AI, such as ChatGPT, influences soft skills and employment opportunities among culturally diverse learners are scarce. It leaves a significant void, given the rapid pace at which technology is affecting both learning and the workplace. Resolving the inconsistencies and questions raised is necessary to create a clearer understanding of the link between the adoption of AI, possessing soft skills, and being employable. This study aims to fill these gaps by investigating the relationship between ESC and soft skills, perceived usefulness, actual use, and employability in mixed-culture environments.

Still, using AI effectively requires people to possess soft skills, such as the ability to adapt, communicate effectively, and cooperate with others. Scholars observe that as technology tasks become automated by AI, human-centered skills have become more critical (Bobitan et al., 2024; Jędrych & Rzepka, 2025). It highlights that soft skills play a crucial role in determining both how AI is utilized and the extent to which people can benefit from it. It is widely accepted that TAM is a valid theory (Wang et al., 2023), but the impact of SK on the relationship between PU, EU, and EM remains unclear. It has been reported in the literature that a gap exists in research on this relationship, particularly within educational and job training contexts (Ciaschi & Barone, 2024). Nowadays, workplaces seek individuals who possess both digital, emotional, and adaptability skills simultaneously (Babashahi et al., 2024). Likewise, utilizing tools that feature AI can enhance your soft skills and increase your employability, such as ChatGPT for developing your CV or using role-play practices for interviews. To fill these theoretical gaps and form a comprehensive understanding of AI and employment readiness, the study examines the relationships among PU, EU, SK, and EM. The model is analyzed using Structural Equation Modeling (SEM) to investigate whether soft skills serve as a link between embracing AI and job performance (Abulail et al., 2025; Subramanian & R, 2024). Problems persist in the area, including uncertainty about how soft skills serve as mediators and inconsistencies in the direct and indirect effects of AI on an individual's employability. Thus, the current study aims to investigate these links through empirical research.

The study investigates how the perceived usefulness (PU) and ease of use (EU) of AI tools influence employability outcomes (EM), and examines the mediating role of soft skills (SK) within this framework. Based on the findings from the literature, this work formulates the research questions, research objectives, hypotheses, and the conceptual framework as follows:

H_1: The perceived usefulness (PU) of AI tools has a positive influence on Employability Outcomes (EM).
H_2: The perceived usefulness (PU) of AI tools positively influences Soft Skills (SK).

H_3: The ease of use (EU) of AI tools positively influences Employability Outcomes (EM).
H_4: The ease of use (EU) of AI tools positively influences Soft Skills (SK).
H_5: Soft Skills (SK) mediate the relationship between the perceived usefulness (PU) of AI tools and Employability Outcomes (EM).
H_6: Soft Skills (SK) mediate the relationship between the ease of use (EU) of AI tools and Employability Outcomes (EM).

This integrated approach contributes to the theoretical foundation for understanding the critical interplay between AI adoption, human capability development, and labor market outcomes.

Conceptual Framework
The conceptual model presented in Figure 1 consists of:

Independent Variables (IV): Employees who experience AI tool functionality as applicable can perceive the tool (such as ChatGPT for CV creation and interview practice) as beneficial to their career development (PU). The ease of use of the AI tool depends on the simplicity of its user interface, and it also requires a clear understanding of how to use it (EU).

Mediator: The implementation of AI-based role-playing and feedback tools enhances students' soft skills, including communication, teamwork, and adaptability, under the category of Soft Skills (SK).

Dependent Variable (DV): The employment outcomes, which reflect job acceptance rates and internship placements, together with readiness assessment metrics, serve as the dependent measure (EM).

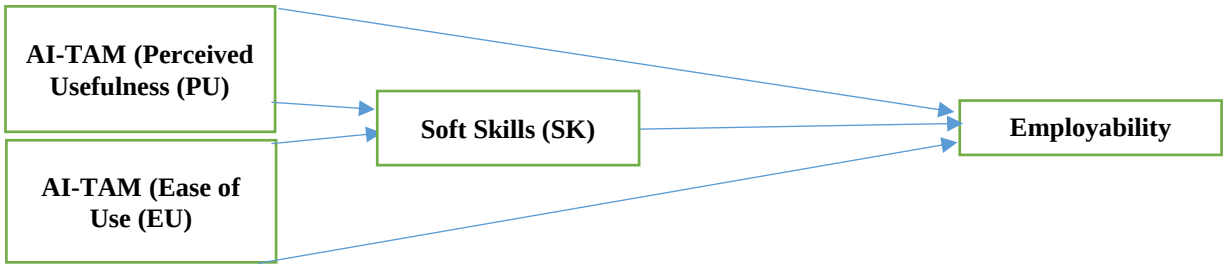

Figure 1. The proposed conceptual Model

MATERIALS AND METHODS

This research examines the impact of Artificial Intelligence (AI) tools on employability outcomes using the Structural Equation Modeling (SEM) approach, specifically Sparse Partial Least Squares (SPLS). The study also examined soft skills as mediators between AI tools and employability. SEM-SPLS effectively serves our model because it demonstrates both strong capabilities in managing complex latent variable relationships and handling data from small to medium-sized samples (Hair et al., 2021). The proposed methodology is presented in Figure 2.

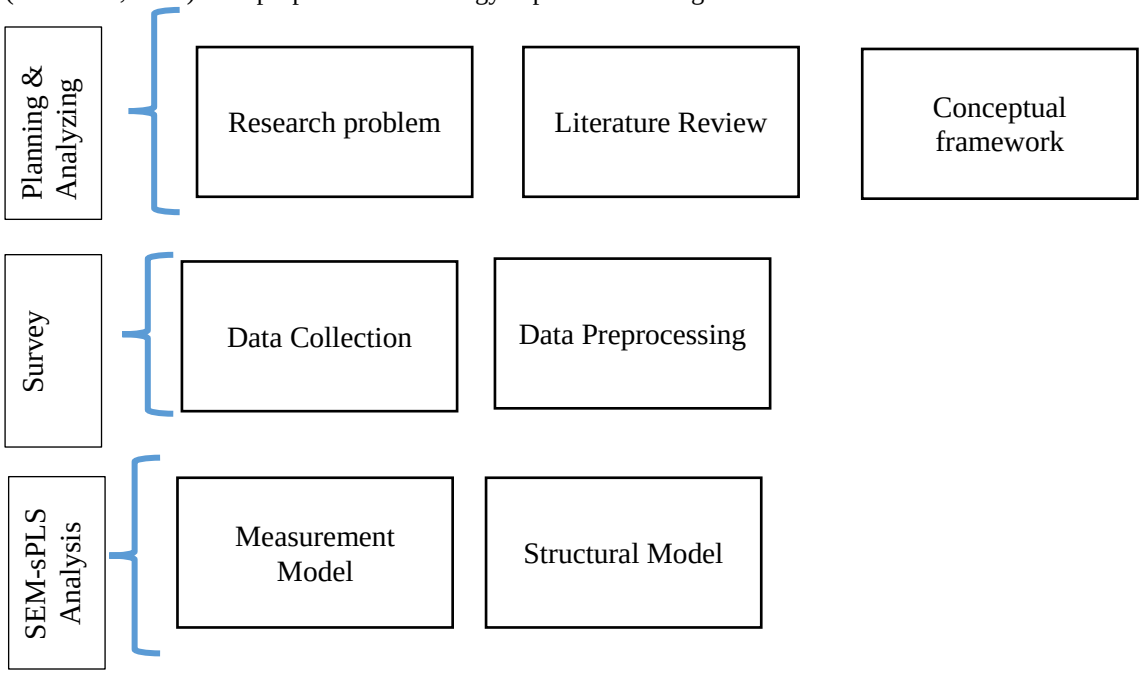

Figure 2. The proposed Methodology

In the planning step of the proposed methodology, as illustrated in Figure 2, the research problem was examined, and a comprehensive literature review was conducted.

Data Collection

The researchers developed a structured questionnaire in Google Forms available at (Survey: TAM and Soft Skills, 2025), and 429 responses have been collected for further processing. The survey research focused on individuals who employed AI tools, including ChatGPT, in either their academic studies or professional work. Every item in the survey was measured on a Likert scale (with 1 indicating "Strongly Disagree" and five indicating "Strongly Agree") to analyze three constructs. The assessment of the perceived usefulness of AI tools forms part of the investigation.
AI Tools – Ease of Use (EU), Soft Skills (SK), Employability Outcomes (EM).
All questions in our Google Form were set up to run on an obligatory mechanism to ensure the completion of the data. The form design required all questions to be completed, thereby eliminating the typical survey problems associated with missing data.

Data Preprocessing

We executed data preprocessing to deliver high-quality input for SEM-SPLS analysis. No normalization procedure was needed because all survey questions used a constant 5-point rating scale. The survey form highlighted complete data consistency because participants could not bypass any required questions. We assessed questionnaire integrity through standard deviation calculations, which addressed potential incorrect or improper use of the survey instruments by participants. The SD measurements fell between 0.3 and 1.7 points, thus meeting the accepted variability standards established by (Hair et al. 2019a; Hair et al. 2019b). The researchers decided to retain all responses because they judged the information suitable for analysis purposes. The data preprocessing results indicate that the dataset meets the requirements to proceed with SEM-SPLS analysis, as its structure remains intact.

Main Steps in SEM-SPLS Analysis

SEM-SPLS analysis comprises two parts: the measurement model (outer model), which uses SPLS to select and estimate the most relevant indicators for each latent construct, and the structural model (inner model), which simultaneously identifies key predictors and estimates path coefficients among those constructs to reveal their interrelationships.

The research framework provides statistical reliability for understanding the employability effects of AI tools that are moderated by soft skills. The SEM-SPLS methodology enables detailed assessments of the connections between these variables, providing actionable insights to educational institutions, policymakers, and workforce developers.

RESULTS AND DISCUSSIONS

Measurement Model

The measurement model evaluates the construct validity and reliability in the evaluation process.

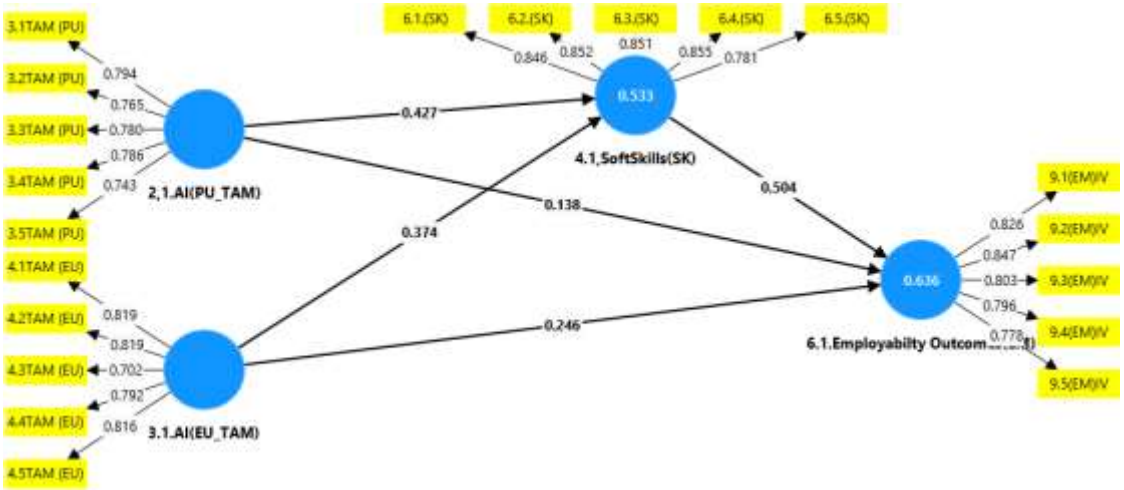

Figure 3. *Factor Loadings*

Figure 3 shows the factor loadings, which serve as an indicator of reliability in this analysis. The research determines reliability through factor loadings, which need to exceed 0.70 for inclusion.

Table 1 shows that the reliability assessment, as measured by Composite Reliability (CR), yields satisfactory results when the CR value is at least 0.70.

Table 1. Construct Reliability

	Cronbach's alpha	(rho_a)	(rho_c)	(AVE)
2,1.AI(PU_TAM)	0.832	0.832	0.882	0.599
3.1.AI(EU_TAM)	0.851	0.861	0.893	0.626

4.1,SoftSkills(SK)	0.893	0.894	0.921	0.701
6.1.Employabilty Outcomes(EM)	0.869	0.870	0.905	0.657

A value for Average Variance Extracted (AVE) above 0.50 proves that the construct describes the main variation within the data. The evaluation of discriminant validity included both the HTMT presented in Table 2 and the Fornell-Larcker criterion presented in Table 3 to separate the constructs from one another.

Table 2. Discriminant reliability HTMT

	2,1.AI(PU_TAM)	**3.1.AI(EU_TAM)**	**4.1,SoftSkills(SK)**	**6.1.Employability Outcomes(EM)**
2,1.AI(PU_TAM)				
3.1.AI(EU_TAM)	0.776			
4.1,SoftSkills(SK)	0.780	0.742		
6.1.Employabilty Outcomes(EM)	0.753	0.766	0.859	

Table 2 shows the discrimination reliability assessment, which utilizes the HTMT (Heterotrait-Monotrait) ratio. All measured values in this analysis remain under 0.90, indicating that the discriminant validity is acceptable. Employability outcomes demonstrate a significant correlation of 0.859 with soft skills, while perceptions of ease of use for AI and perceived AI impact show moderate relationships with all other constructs.

Table 3. Forner laker

	2,1.AI(PU_TAM)	**3.1.AI(EU_TAM)**	**4.1,SoftSkills(SK)**	**6.1.Employabilty Outcomes(EM)**
2,1.AI(PU_TAM)	0.774			
3.1.AI(EU_TAM)	0.660	0.791		
4.1,SoftSkills(SK)	0.674	0.656	0.837	
6.1.Employabilty Outcomes(EM)	0.641	0.668	0.759	0.810

Table 3 demonstrates that the Fornell-Larcker table establishes discriminant validity through comparisons between off-diagonal inter-construct correlation values and the square roots of AVE values displayed on the table's diagonal. The Fornell-Larcker assessment reveals that diagonal values exceed off-diagonal correlations, which confirms the discriminant validity results. Intangible competencies (0.837) and cognitive views regarding AI technologies (0.810) jointly affect employment readiness.

Structural Model

This model examines Hypotheses and the relationships between the latent constructs of PU, EU, SK, and EM. The following steps were taken: Figure 4 illustrates the bootstrapping process.

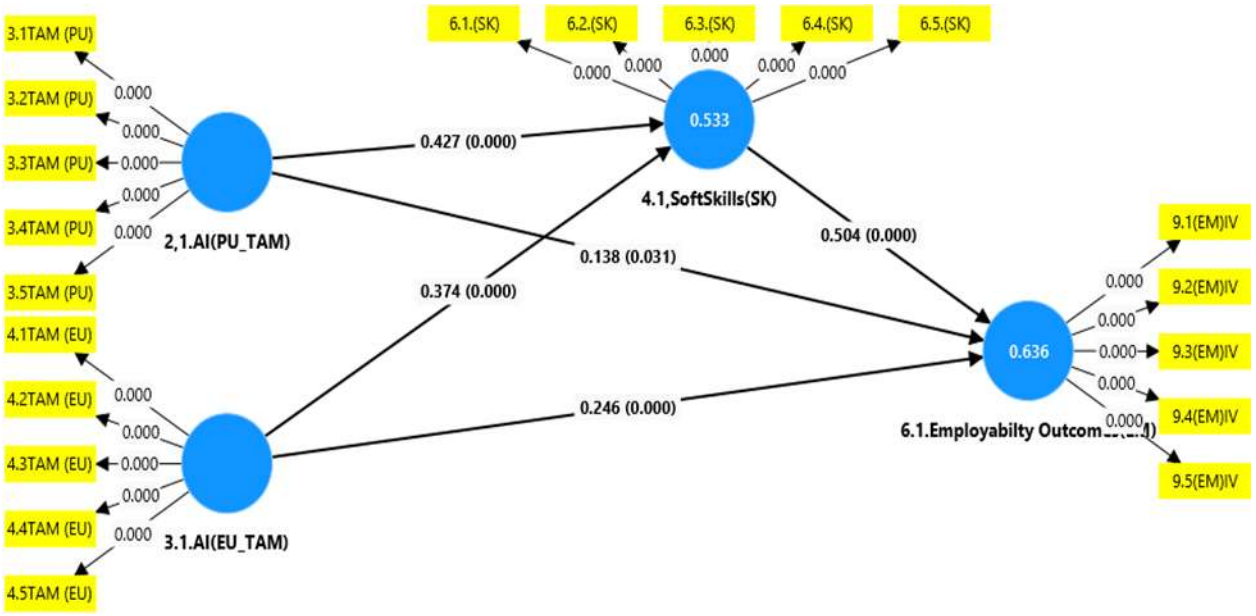

Figure 4. Bootstrapping Output

Figure 4 shows the evaluation of relationships between constructs that occurred through path coefficient estimation. The Bootstrapping with 10,000 resamples establishes the statistical significance of the paths, maintaining a p-value of less than 0.05.

Table 4. Path coefficient

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
2,1.AI(PU_TAM) -> 4.1,SoftSkills(SK)	0.427	0.433	0.082	5.199	0.000
2,1.AI(PU_TAM) -> 6.1.Employabilty Outcomes(EM)	0.138	0.142	0.074	1.871	0.031
3.1.AI(EU_TAM) -> 4.1,SoftSkills(SK)	0.374	0.370	0.096	3.897	0.000
3.1.AI(EU_TAM) -> 6.1.Employabilty Outcomes(EM)	0.246	0.246	0.073	3.365	0.000
4.1,SoftSkills(SK) -> 6.1.Employabilty Outcomes(EM)	0.504	0.503	0.073	6.890	0.000

Table 4 analyzes path coefficients to determine the relationships between hypotheses through T-statistics, although p-values serve as validation metrics. The research accepts all hypotheses when p values fall below 0.05. Soft Skills (β = 0.427, p = 0.000) and Employability Outcomes (β = 0.138, p = 0.031) receive significant impacts from Perceived usefulness (PU_TAM). Both Soft Skills (β = 0.374, p = 0.000) and Employability (β = 0.246, p = 0.000) are influenced by perceived ease of use (EU_TAM). Soft Skills have a substantial effect on Employability Outcomes, as indicated by the beta value of 0.504 and the p-value of 0.000.

Table 5. Specific indirect effect

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
2,1.AI(PU_TAM) -> 4.1,SoftSkills(SK) -> 6.1.Employabilty Outcomes(EM)	0.216	0.219	0.057	3.765	0.000
3.1.AI(EU_TAM) -> 4.1,SoftSkills(SK) -> 6.1.Employabilty Outcomes(EM)	0.189	0.185	0.051	3.704	0.000

Table 5 demonstrates that the established specific indirect effects validate that Soft Skills (SK) function as an essential mediator connecting AI constructs to Employability Outcomes (EM). The total impact of AI Perceived Usefulness (PU_TAM) on Employability Outcomes (EM) is mediated by Soft Skills (SK), with a statistically significant effect of 0.216 (p = 0.000). The calculated impact from Perceived Ease of Use (EU_TAM) to EM through SK is 0.189 (p = 0.000). The results indicate significant improvements in job readiness due to expertise and development in soft skills. Soft skills act as a critical mediator, enhancing PU_TAM from 0.138 to 0.354, resulting in a 56.1% additional impact, while also boosting EU_TAM from 0.246 to 0.435, which leads to a 76.8% increase in total effect.

CONCLUSIONS

The proposed work aimed to investigate the role of AI tools, such as ChatGPT, in enhancing people's career abilities and skills. Relying on the Technology Acceptance Model (TAM), the study investigated how workers' opinions on the usefulness and user-friendliness of AI technologies influence their job preparation. It is demonstrated that utilizing AI enables individuals to acquire essential, transferable skills, including public speaking, adapting to change, and problem-solving. Developing these capabilities significantly enhances a person's prospects for a job and future employment opportunities. It was shown that those who view AI tools as beneficial and straightforward to use tend to enjoy skill-based learning more, which helps them achieve better job results. A significant advance in this paper is the presentation of a framework that combines TAM variables and soft skills with indicators of employability to guide the use of AI in education and the workplace. This study goes beyond regular methods, viewing AI as a tool that enhances soft skills in culturally diverse settings.

Adopting the Technology Acceptance Model (TAM) provides a robust framework for examining how soft skills and employability influence the uptake of AI-based learning and work tools, offering critical guidance for educators, HR planners, and AI developers when designing inclusive, skill-oriented training that aligns with evolving labor market needs. For managers, this implies incentivizing the integration of AI tools into employee development programs to strengthen soft skills, continuously assessing user experience and engagement through TAM constructs, and iteratively refining AI systems based on those insights. By linking AI-enhanced learning initiatives to broader workforce adaptation goals, organizations can ensure that their training investments yield measurable gains in both individual performance and organizational resilience.

This study lacks sufficient participants from diverse regions, which limits its scope and generalizability. Strengths and weaknesses in culture, effective organization, and the utilization of digital tools were not considered, which may limit the relevance of the findings.

Future investigations should assess the lasting impact of AI-driven soft skill development across multiple industries and locations. Experts are advised to consider other potential moderating factors, including organizational culture, leadership support, and the type of industry. Adding aspects of emotional intelligence or cross-cultural competency could enhance the model's effectiveness in international teams.

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