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ORIGINAL CONTRIBUTION

Nexus of Human-AI Trust Equation: Competence, Ethics, and Self-Efficacy as Drivers of Career Growth and AI-Supported Decision Involvement

Baoxin Zhang[1], Mahwish Anjam[2], Sonakshi Ruhela[3], Umer Zaman[4]*

[1]Woosong University, Daejeon, South Korea

[2]School of Business and Humanities, Curtin University, Dubai, United Arab Emirates

[3]Department of Liberal Arts, Rochester Institute of Technology, Dubai, United Arab Emirates

[4]Endicott College of International Studies, Woosong University, Daejeon, South Korea

Abstract— Generative artificial intelligence is increasingly being incorporated into education and career development, raising important questions about how trust influences user participants, ethical awareness, and career-related behavior. However, how trust translates into effective AI use under different psychological mechanisms and contextual conditions remains insufficiently understood. This study aims to examine how trust in generative AI influences career advancement behaviors and participation in AI-integrated decision-making, as well as the mediating roles of digital self-efficacy and AI ethical awareness, and the moderating role of AI training exposure. Data were collected from 365 international students over three months using validated survey instruments measuring trust in AI, digital self-efficacy, ethical awareness, and behavioral outcomes. Purposive sampling strategy targeted students engaged with AI-based learning, and the data were analyzed using SmartPLS-based Structural Equation Modeling (SEM). The results show that trust in generative AI has significant direct effects on career advancement behaviors and participation in AI-integrated decision-making. Digital self-efficacy and AI ethical awareness both serve as significant mediators in these relationships. In addition, AI training exposure significantly moderates the effects of trust on digital self-efficacy and ethical awareness. This study demonstrated that trust in generative AI exerts a pivotal influence through digital self-efficacy and AI ethical awareness, thereby promoting individuals' career advancement behaviors and participation in AI-integrated decision-making. The findings further indicate that the sustainable and responsible use of generative AI depends on the synergistic effects of trust, self-efficacy, and ethical awareness within supportive training environments.

Index Terms— Trust in Generative AI, Digital self-efficacy, AI ethical awareness, Career advancement behaviors, AI-integrated decision-making

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Introduction

The Generative AI (GenAI) technologies have rapidly diffused globally, and they have fundamentally changed the process of work, learning, and decision-making (Dang & Li, 2025; Mendy et al., 2025; Tsou, 2025). By converting data into actionable insights, the technologies are transforming data into a means of how people learn, cooperate, and develop their careers (Amoozadeh et al., 2024). Artificial intelligence solutions in industries and educational institutions are rapidly being embraced on a global scale to promote efficiency, creativity, and strategic choices (Albashrawi, 2025; Law, 2024). Meanwhile, states and companies are also investing large sums in control systems and AI ethics to provide a secure adoption

*Email: umerzaman@endicott.ac.kr

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(Solaiman, 2024). In this broader global context, the comprehensive concept of AI use for professional competence and decision support extends beyond technical considerations (Hughes et al., 2025; Solaiman, 2024), but also to develop trust in AI systems and to demonstrate ethical awareness in their use. The digital infrastructure, together with the ambitious AI policy in the Korean example, has led the country to become one of the biggest research, adoption, and innovation centers in AI (Ganescu & Passerat-Palmbach, 2024). The adoption of AI in educational and work settings has been rapidly increasing among Korean students (Dai et al., 2025), especially international student (Cho & Ofosu-Anim, 2025), whereby the level of AI trust is perceived to influence their readiness to participate in the AI-enhanced task and their chances of career growth (F. Huang et al., 2024). The two-pronged approach that takes into account and incorporates the global AI revolution with the unique Korean digital space (So et al., 2024) provides a critical situation to analyze the relationship between confidence in GenAI, professional life, and cognition of decision-making (Cho & Ofosu-Anim, 2025; Solaiman, 2024; Wang & Kim, 2025).

The importance of trust in AI has been generally acknowledged as the primary factor in the user adoption rate, the involvement in decision-making, and the professional growth results (Albashrawi, 2025; Dang & Li, 2025). Significantly, researchers have found that the perceived reliability, transparency, fairness, and security influence the trust in AI and are the key determinants of people accepting the recommendation and willingness to make AI-supported decisions (Huynh, 2024). Prior research in workplaces has also suggested that employees who trust AI systems are more willing to adopt the results of AI into their work processes and show improved job performance and professional growth (Mai & Nguyen, 2025). In addition to this, self-efficacy has also played a prominent role in psychology because it moderates the association between AI trust and actual usage behaviors in the real world (Montag et al., 2023). Meanwhile, the regulation of responsible AI use requires ethical consciousness (Migdadi et al., 2024). Collectively, AI trust has been demonstrated to influence participation and professional growth under various circumstances, both cognitively and ethically (Dang & Li, 2025; Montag et al., 2023).

Despite the increasing body of literature, understanding of the relationship among trust in GenAI, participation in decision-making, and career development behaviors remains limited and gaps (Solaiman, 2024; Tsou, 2025). Most prior studies have examined trust in AI in general or in specific application domains, such as healthcare or finance, without distinguishing the unique dynamics of generative AI, which introduces complex challenges due to its creative and probabilistic outputs (Huynh, 2024; Montag et al., 2023). Moreover, existing literature also tended to focus on either behavioural outcomes, such as technology adoption, or ethical concerns, such as bias awareness (Svestkova et al., 2025). In particular, the mediator roles of digital self-efficacy and AI ethical awareness interrelationship between trust in AI and future career growth (Thorne, 2024). Although the moderating effect of training has been well-established in the general technological adoption frameworks, trust-self-efficacy and trust-ethical awareness pathways remain unexplored in the AI contexts (Abuadas & Albikawi, 2025).

The other gap that is critical is the contextual and cultural aspect of trust in AI adoption and use. Most existing studies have been conducted in the Western context (Albashrawi, 2025), with limited attention to individuals operating in cross-cultural academic and work settings where AI actively informs decision-making (Ahmad, 2024). As the example of Korean international students can operate within digitally advanced ecosystems abroad while remaining closely connected with Korea's rapidly evolving AI-driven environment (So et al., 2024; Wang & Kim, 2025). This unique position may influence their perception of the trust and justice, openness, and security of AI, and how their attitudes would be used regarding professional actions (AlQahtani, 2025). Empirical studies are, however, scarce regarding the interaction of trust, ethics, self-efficacy, and training exposure in the conditions of forming engagement and professional growth in the AI environment, particularly in culturally diverse settings (Abbas et al., 2025; Dai et al., 2025; Hughes et al., 2025).

The paper will examine the interrelations between trust in generative AI, digital self-efficacy, AI-awareness of ethics, participation in AI-enriched decision-making, and career advancement behavior, with additional consideration of the mediating role of digital self-efficacy and AI-awareness of ethics and the moderating role of AI training exposure. Specifically, the proposed research will: (1) test the indirect role of trust in GenAI on AI-integrated decision-making and career development behaviors, (2) test the role of digital self-efficacy as the mediator, (3) test the role of awareness of AI ethical Risks as a mediator, and (4) evaluate the role of AI training exposure as a moderator.

This study offers both theoretical and practical contributions by integrating trust, self-efficacy, moral awareness, and training exposure within a single theoretical framework. Practically, the results inform policymakers, teachers, and business owners on how to structure AI education and ethical policies that foster trust in AI (So et al., 2024; Wang & Kim, 2025), encourage responsible use, and support their career development (Korkmaz et al., 2025), while emerging body of literature on human-AI partnerships and career development sustainability in the generative AI context.

Literature Review

Theoretical framework supporting the research

Theoretical assumptions underlying the investigation of the inter-relations among trust in generative AI, digital self-efficacy, ethical knowledge of AI, involvement in AI-based decision-making situation, and career advancement development related activities are established in the Technology Acceptance Model (TAM) (Albashrawi, 2025; Tsou, 2025), Social Cognitive Theory (SCT) (Mendy et al., 2025), and Ethical Awareness grounded in (Rest, 1986), which provide a combination of conceptually blurred explanations of how individuals engage with advanced AI technologies in the

workplace and decision-making contexts (Dai et al., 2025; Solaiman, 2024). TAM assumes that the attitudes towards a technology as reliable, fair, transparent, and safe affect behavioral intentions and behaviors through attitudes towards using the technology (Davis, 1989; Venkatesh & Davis, 2000). In the context of generative AI, trust drivers are crucial motivators to adopt in the decision-making process and the use of AI for career development (Montag et al., 2023). SCT highlights the contribution of self-efficacy confidence in performing specific tasks toward bridging attitudes and behaviour (Bandura, 2001). When individuals trust AI systems, it enhances their digital self-efficacy and promotes effective use of AI tools (Dang & Li, 2025; Montag et al., 2023; Tsou, 2025), while AI training exposure further reinforces this process through skill and self-confidence development (Migdadi et al., 2024). Grounded in Rest (1986) four-component model of moral behavior, ethical awareness further suggests that trust in AI may heighten individuals' sensitivity to ethical considerations, such that users who trust the moral integrity of AI systems are more attentive to critically inspect their outputs for bias, fairness, and transparency (Dai et al., 2025; Jobin et al., 2019; Mendy et al., 2025). This kind of ethical awareness not only results in responsible decision-making but also helps to sustain career development behaviors in line with professional integrity (Kong et al., 2023). Also, one can enjoy the moderating role of AI training exposure through the prism of the Knowledge-Attitude-Behavior (KAB) model (Liu et al., 2024), to which knowledge acquisition is an appropriate process to convert positive attitudes to proper and ethical action (McGuire, 2014). Combining these views, the model under research postulates that trust in generative AI has both direct and indirect positive impact on the decision-making and career development behavior involving AI integration by the mediating effects of digital self-efficacy and AI ethical awareness, and AI training exposure reinforces the trust-mediator associations. The conceptual framework of the problem is presented in Figure 1, which defines the suggested direct, mediating, and moderating relationships between the constructs.

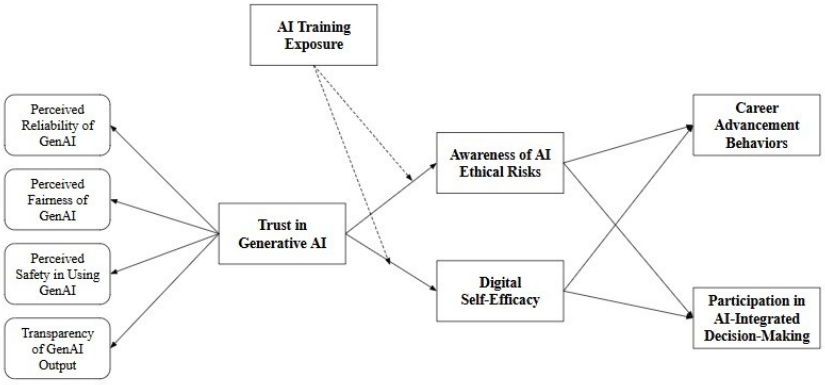


Fig. 1 *Conceptual framework*

Hypothesis development

Trust in generative AI is conceptualized as perceptions of reliability, fairness, absence of bias, transparency of output, and safety of use (Dang & Li, 2025; Montag et al., 2023), which affect how individuals integrate AI into their work-related professional development activities (Amoozadeh et al., 2024). Perceived reliability involves the consistency and correctness of information generated by AI, influencing assurance in using AI tools for professional decision-making concerning careers (Baek & Kim, 2023). Perceptions of fairness and lack of bias in generative AI recommendations constitute a crucial basis for evaluating their objectivity and fairness, which in turn influence the acceptability of AI as a valid career counselling tool (Wang & Kim, 2025). Transparency of AI results allows users to see the justification for AI-generated conclusions, which enhances trust and promotes the application of these conclusions in business strategies (Zhang et al., 2025). Perceived safety in using AI is attributed to data security and the absence of harmful consequences, raising the likelihood of a user's intention to use AI in employment planning (Ganescu & Passerat-Palmbach, 2024).

Empirical evidence indicates that trust in AI technologies is associated with the adoption of AI-enabled tools for career-related learning (Dang & Li, 2025), professional development, and advancement-oriented activities (Cho & Ofosu-Anim, 2025). Organizational studies have found that a high level of trust in AI technologies enhances workplace productivity and supports individuals' ability to adapt to emerging industry trends (Hughes et al., 2025; Solaiman, 2024), thereby contributing to improving career performance (Mai & Nguyen, 2025). The actual state of the research, especially the research conducted in the sphere of education, shows that individuals are more willing to proceed with learning and research new methods of advancing their careers once they are assured that AI is secure, fair, open, and reliable (Marimon et al., 2025).

H1. Trust in GenAI is positively associated with career advancement behaviors.

Trust in generative AI also dictates the level of individuals' participation in AI-supported decision-making, as precepted by reliability, fairness, transparency, and safety (Lin et al., 2025). The reliability enables the coherent AI output and guarantees individuals to be active participants in the decision-making process by using AI tools (Abuadas & Albikawi, 2025). The aspect of fairness and non-bias confirms that the AI-supported

decisions are right and impartial, so that more parties can participate in the group decision-making process (Artene et al., 2024). Transparency helps to create similarity of knowledge about AI thinking and facilitates the willingness and trust to collaborate with AI, making difficult decisions (Babbar & Rani, 2025). With the perception of safety, the fear of misusing information and negative impacts is relieved (Dang & Li, 2025; Jobin et al., 2019), allowing users to interact more comfortably.

The evidence of organizational and educational settings confirms that the trust in AI-based collaborative work (Dang & Li, 2025; Mendy et al., 2025), including strategic planning, research work, and problem solving (Mai & Nguyen, 2025), exists. The generation of AI through trust makes AI a partner in decision-making and not a substitute for human judgment (Ferhataj et al., 2025). In this way, it is necessary to enhance the quantity and quality of contributions in cooperative environments, as well as to significantly make the inclusion, active, and effective involvement in AI-based decision-making more inclusive, active, and efficient (Baek & Kim, 2023; Migdadi et al., 2024).

H2. Trust in GenAI is positively associated with participation in AI-integrated decision-making.

Digital self-efficacy is the perception of people that they can successfully use the impact of digital technologies, such as generative AI, to break down, assess, and apply AI-generated information to work (Abuadas & Albikawi, 2025). Digital self-efficacy in the context of generative AI presupposes the ability to operate AI interfaces, critically evaluate the products of AI (Wang & Kim, 2025), and implement AI suggestions in everyday activities. Reliability, fairness, transparency, and safety are trusted in generative AI, which lowers uncertainty and the perception of risk and thus promotes the attitude of people towards their power to utilize AI in the most effective manner (F. Huang et al., 2024; Kalkim et al., 2024). This greater self-efficacy creates proactive career development activities, such as skills acquisition, adaptive work practices, and strategic application of emerging technologies, which build larger career adaptability and professional skills (Paredes-Aguirre et al., 2024; Shaban et al., 2024).

It is based on this approach that digital self-efficacy is one of the central mediator mechanisms where trust in generative AI results in involvement in AI-equipped decision-making (Ibrahim & Aldawsari, 2023; Liu et al., 2024). Such decision-making is more than just willingness, and it is an expression of the self-confidence to cooperate with AI in the important task of critically assessing and incorporating algorithmic recommendations into final decisions (Migdadi et al., 2024). Confidence in the perceived reliability, fairness, openness, and security of AI as a decision-support system (Getenet et al., 2024) subsequently increases the confidence and active involvement of users in the use of AI-assisted decision-making (Altindağ Kumaş & Sardohan Yildirim, 2024). It was found that a high level of digital self-efficacy ensures a higher level of substantive contribution in the collaborative work with advanced technology by minimizing the uncertainty, stimulating the informed interaction with AI, and increasing the collaborative productivity (Dang & Li, 2025; Mendy et al., 2025).

H3. Digital self-efficacy mediates the positive relationship between trust in GenAI and career advancement behaviors.

H4. Digital self-efficacy mediates the positive relationship between trust in GenAI and participation in AI-integrated decision-making.

The concept of AI ethical awareness implies individuals' recognition and awareness of Rest (1986) fourth ethical standards that can be related to AI system development and usage (Abuadas & Albikawi, 2025). It involves a dynamic interaction with AI outcome, social and professional implications (Ferhataj et al., 2025), thereby encouraging adoption and ethical engagement with generative AI when the system is perceived as impartial and safe (Migdadi et al., 2024). Trust-based understanding of AI can directly foster career development behaviors by promoting responsible and ethically aligned use of AI technologies (Mohammed et al., 2025). It is demonstrated that individuals with higher ethical awareness of AI tend to adopt a more cautious approach to using AI across career-related activities, including reputational outcomes, employment, skill, and career development (Zhu et al., 2025). Their colleagues and superiors place more confidence in them, and they have a chance to advance their careers using the demonstration of competence and ethical responsibility (Dang & Li, 2025).

The ethical awareness is also critical in facilitating participation in the AI-embodied decision-making (X. Li et al., 2025). It encourages ethical interaction when users believe that generative AI is fair, transparent, reliable, and safe,which in turn prompts users to think more carefully about the role of AI in decision-making and how its use affects decision quality and inclusiveness (Pant et al., 2024). It is scientifically proven that high AI ethical awareness persons play a more significant role in collaborative contexts without compromising decision-making processes and comply with principles of fairness, inclusiveness, and accountability (Abuadas & Albikawi, 2025). They make it easier to balance the responsibility and efficiency, and yield not only technically valid, but also socially justified outcomes (Zhu et al., 2025). AI ethical awareness serves as a mediating mechanism through which trust in generative AI affects career advancement behaviors and participation in AI-integrated decision-making (Lin-Lewry et al., 2024).

H5. AI ethical awareness mediates the positive relationship between trust in GenAI and career advancement behaviors

H6. AI ethical awareness mediates the positive relationship between trust in GenAI and participation in AI-integrated decision-making

The level of exposure to AI training, referring to individuals' prior formal or informal learning experience with the assistance of AI technologies, is likely to condition how trust in generative AI is formed and expressed in digital capability (Amoozadeh et al., 2024; Ridwan et al., 2025). However, the strength of this association may depend on prior AI-related education (Hughes et al., 2025; Law, 2024). Beyond technical skills, such AI training provides individuals with contextual knowledge of understanding AI systems, thereby enabling individuals to translate trust in AI into proficient and assured use (Artene et al., 2024). Empirical research evidence indicates that specific technology training reinforces the connection between positive technology attitudes and digital self-efficacy by improving practical application skills (Dissanayake & Al-Sharify, 2025). In the context of AI, higher levels of training exposure amplify the moderating effect of training on the trust–self-efficacy relationship

(Heo, 2025).

Exposure to AI training may add more detail to the relationship between trust in generative AI and AI ethical awareness (Mendy et al., 2025). It is the capacity to identify and manage such ethical issues as bias, transparency, accountability, and fairness in AI products (Babbar & Rani, 2025), and trust promotes thinking about the morale and other things that AI consumption may impose on society (Kaggwa et al., 2024). However, they are not capable of translating trust into effective ethical awareness without training, since they might not have the cognitive frameworks (Solaiman, 2024). Ethics-oriented training and regulatory guidance tend to be part of the AI training, and they allow technical competence to be combined with the rules of responsible usage (A. A. Khan et al., 2023; Mendy et al., 2025). The study of AI ethics concludes that better-trained people are better able to identify the risks of any ethics and use mitigation strategies to address these risks, especially when they already have a positive disposition towards the technology (Mohammed et al., 2025).

H7. AI training exposure moderates the effect of trust in GenAI on digital self-efficacy, such that the effect is stronger when AI training exposure is higher.

H8. AI training exposure moderates the effect of trust in GenAI on AI ethical awareness, such that the effect is stronger when AI training exposure is higher.

Methodology

Research design

The research used a quantitative, cross-sectional research design to test the intercorrelations among trust in generative AI, digital self-efficacy, AI ethical awareness, participation in AI-integrated decision-making, and career advancement behaviors. A quantitative design was considered appropriate because it allows statistical testing of hypothesized relationships using standardized data from a large sample (Cresswell, 2013; Manzoor et al., 2021; Oraee et al., 2025). The proposed research model with mediating and moderating relationships necessitates robust statistical methods to analyze complex inter-variable relationships.

Population

The target group was comprised of students who were currently undertaking higher education programs and had experience with AI-enabled educational or work environments (Shahzad et al., 2025). The most suitable population in this study is students, as they are the first to use the new technologies, and they will become the future workforce whose professional development is likely to be affected by the development of AI (Davis, 1989).

Sample size and sampling approach

The final sample consisted of 365 participants, including international students who experience the use of generative AI platforms in their academic life, which is regarded as enough to analyze it with the PLS-SEM in accordance with the 10-times rule, as well as the guidelines of the power analysis (J. F. Hair et al., 2011). According to the 10-times rule, the minimum sample size should be at least ten times the maximum number of structural paths to any constructs in the model (Cengiz & Peker, 2025). The purposive sampling method was utilized to recruit students with prior experience exposure to generative AI tools in their studies or work. This non-probability ensured formed responses on trust in GenAI, decision-making participation, and career advancement behaviors (Shahzad et al., 2025).

Data collection

The data information was gathered using a pre-coded online questionnaire, which included self-reported data. Electronic distribution has been chosen because it is efficient in reaching a geographically spread student sample and because it is easy to respond to by engaging in electronic platforms (L. Huang et al., 2025; Macedo et al., 2024), which is also in line with the AI-oriented study. In the previous research, the questionnaire items were pre-determined to allow content validity and comparison with published research. They were all measured using multi-item Likert-type scales that used prior literature to create trust in GenAI, digital self-efficacy, AI ethical awareness, AI-integrated decision-making engagement, and career advancement behaviors (Roffia et al., 2025). A small sample of students was used in the pilot test of the survey to ensure that the wording was complete and the items were understood clearly. All the participation was voluntary, and responses were collected in a manner that ensured anonymity to enable one to respond freely.

Data analysis

SmartPLS was used to analyze data to perform the Partial Least Squares Structural Equation Modeling (PLS-SEM). This method can be used to estimate multifactor (with several latent constructs) and multimediator and moderator models (Legate et al., 2023; M. Li & Li, 2025b; Refugio

Romo-Gonzalez et al., 2018) and can be applied to test theory in a way that involves prediction (Hair Jr et al., 2020). The analysis was carried out at two levels: (1) measurement model to test the reliability, validity, and internal consistency of the scales; (2) testing the structural model hypothesis to test direct, mediating, and moderating relationships. The path coefficients had standard errors and significance levels that were obtained through bootstrapping, 5,000 resamples.

Results

Table I findings indicate that the internal consistency reliability of all constructs is high. The internal consistency reliability of all constructs is high, and both Cronbach's Alpha and composite reliability (ρc) are acceptable values that are higher than the advised 0.70 variance level of all the variables (J. Hair & Alamer, 2022; Legate et al., 2023), which is a sign of a reliable measurement model. Moreover, all constructs have AVE values that are greater than the necessary minimum value of 0.50, giving adequate convergent validity (Henseler et al., 2016). The maximum AVE belongs to AI training exposure (0.868), which implies that this construct explains a considerable percentage of variance in its indicators. The AVE of perceived fairness and non-bias of generative AI is also high (0.807), which is an indication of good measurement validity. On balance, these results are good indicators of the reliability and validity of the measuring model.

Table I
Variables reliability and validity

Construct	Cronbach's Alpha	Composite Reliability (ρc)	Average Variance Extracted (AVE)
AI Ethical Awareness	0.877	0.911	0.672
AI Training Exposure	0.848	0.929	0.868
Career Advancement Behaviors	0.884	0.916	0.687
Digital Self-Efficacy	0.881	0.910	0.629
Participation in AI-Integrated Decision-Making	0.852	0.900	0.693
Perceived Fairness and Non-Bias of Generative AI	0.761	0.893	0.807
Perceived Reliability of Generative AI	0.866	0.918	0.789
Perceived Safety in Using Generative AI	0.815	0.890	0.729
Transparency of Generative AI Output	0.723	0.878	0.783

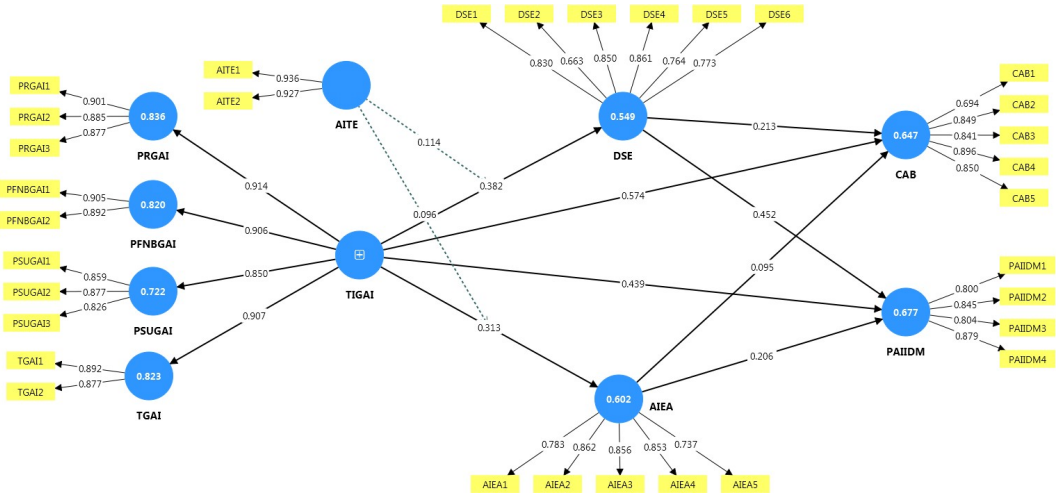


Fig. 2 *Estimated model*

The CFA results in Table II and Figure 2 show that all measurement items load strongly onto their respective constructs, with standardized factor loadings exceeding the recommended 0.60 threshold (Hair Jr et al., 2020; M. Li & Li, 2025a). All but a few of the items register loadings over 0.80, which implies that the indicator variables capture strongly the underlying latent constructs for which they were intended (Oraee et al., 2025). For instance, AI Training Exposure items (AITE1 = 0.936, AITE2 = 0.927) show great loadings, and thus the construct is clearly captured by the measures. Likewise, items capturing perceived reliability of generative AI (ranging from 0.877 to 0.901) affirm measurement quality as high. These findings validate the convergent validity of the model and establish that the indicators do measure their respective intended constructs effectively.

Table II
Confirmatory factor analysis

	AI Ethical Awareness	AI Training Exposure	Career Advancement Behaviors	Digital Self-Efficacy	Participation in AI-Integrated Decision-Making	Perceived Fairness and Non-Bias of Generative AI	Perceived Reliability of Generative AI	Perceived Safety in Using Generative AI	Transparency of GenAI Output
AIEA1	0.783								
AIEA2	0.862								
AIEA3	0.856								
AIEA4	0.853								
AIEA5	0.737								
AITE1		0.936							
AITE2		0.927							
CAB1			0.694						
CAB2			0.849						
CAB3			0.841						
CAB4			0.896						
CAB5			0.850						
DSE1				0.830					
DSE2				0.663					
DSE3				0.850					
DSE4				0.861					
DSE5				0.764					
DSE6				0.773					
PAIIDM1					0.800				
PAIIDM2					0.845				
PAIIDM3					0.804				
PAIIDM4					0.879				
PFNBGAI1						0.905			
PFNBGAI2						0.892			
PRGAI1							0.901		
PRGAI2							0.885		
PRGAI3							0.877		
PSUGAI1								0.859	
PSUGAI2								0.877	
PSUGAI3								0.826	
TGAI1									0.892
TGAI2									0.877

Table III
Discriminant validity (HTMT)

	AIEA	AITE	CAB	DSE	PAIIDM	PFNBGAI	PRGAI	PSUGAI	TGAI
AI Ethical Awareness									
AI Training Exposure	0.800								
Career Advancement Behaviors	0.717	0.742							
Digital Self-Efficacy	0.800	0.737	0.739						
Participation in AI-Integrated Decision-Making	0.751	0.775	0.800	0.800					
Perceived Fairness and Non-Bias of Generative AI	0.800	0.750	0.800	0.791	0.844				
Perceived Reliability of Generative AI	0.712	0.620	0.792	0.712	0.821	0.800			
Perceived Safety in Using Generative AI	0.598	0.699	0.834	0.550	0.755	0.800	0.768		
Transparency of Generative AI Output	0.683	0.655	0.805	0.723	0.810	0.800	0.800	0.800	

The HTMT values in Table III validate the discriminant validity of the constructs, with all of them being below the suggested maximum cut-off of 0.85 (J. F. Hair et al., 2019). This shows that each construct is empirically different from the rest. For instance, HTMT between AI ethical awareness and career advancement behaviors is 0.717, and between perceived reliability of generative AI and digital self-efficacy is 0.712, both within normal bounds. The results confirm that the constructs in the study represent distinct dimensions of the research model without substantial conceptual redundancy.

R-square values presented in Table IV reflect the high explanatory strength of the model. AI training exposure has the maximum R^2 of 0.647, reflecting that most of its variance is explained through predictors in the model. AI ethical awareness (R^2 = 0.602) and Digital Self-Efficacy (R^2 = 0.677) also reflect strong explained variance, reaffirming that the model is predicting these mediators. Career Advancement Behaviors possess an R^2 value of 0.549, signifying moderate prediction potency. The Q^2 values for all the criteria are greater than zero, signifying predictive relevance of the model, and the SRMR value of 0.080 is well within the range for acceptable fit for the model, signifying overall structural model adequacy (J. F. Hair et al., 2019).

Table IV
R-square statistics model goodness of fit statistics

	R-square	R-square adjusted	Q^2	SRMR
AI Ethical Awareness	0.602	0.599	0.592	0.080
AI Training Exposure	0.647	0.644	0.637	
Career Advancement Behaviors	0.549	0.546	0.533	
Digital Self-Efficacy	0.677	0.674	0.606	

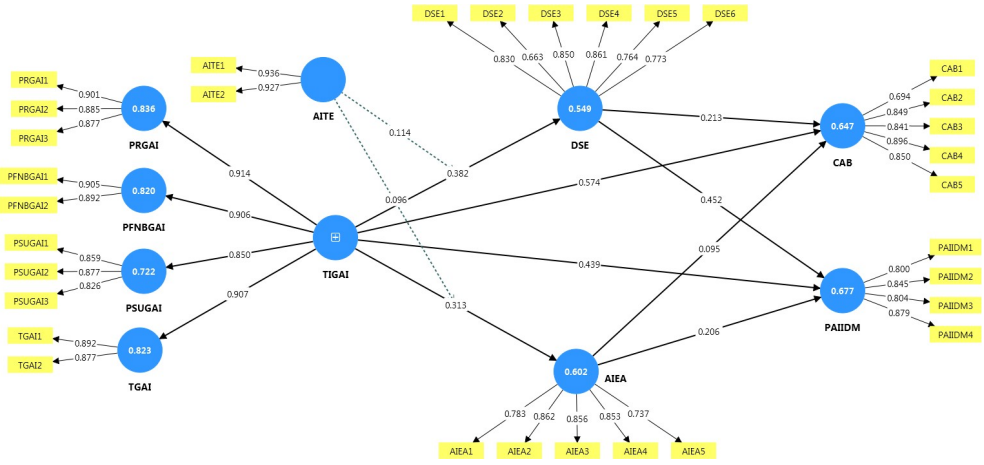


Fig. 3 *Structural model for path analysis*

Path analysis output in Table V shows that all the hypothesized links in the structural model are significant and supported statistically. The direct influence of Trust In generative AI (TIGAI) on Career Advancement Behaviors (CAB) is high, with a beta of 0.574, a *t*-value of 11.691, and a *p*-value of 0.000, which shows a large positive effect. Similarly, TIGAI has a direct Positive Influence on Involvement in AI-Integrated Decision-Making (PAIIDM), and its beta is 0.439, *t*-value is 7.691, and *p*-value is 0.000. The mediation test confirms that digital self-efficacy (DSE) is a significant

mediating variable between TIGAI and CAB (*β* = 0.081, *t* = 3.384, *p* = 0.000) and PAIIDM (*β* = 0.172, *t* = 5.562, *p* = 0.000) and demonstrates the significance of the competence of the users in turning the trust into action. Similarly, the TIGAI and CAB (*β* = 0.067, *t* = 2.815, *p* = 0.005) and PAIIDM (*β* = 0.095, *t* = 3.102, *p* = 0.002) have significant relationships with AI ethical awareness, both with the moderator of AI Ethical Awareness (AIEA). Moderation analysis further demonstrates the moderated effect of TIGAI on AIEA (*β* = 0.096, *t* = 3.416, *p* = 0.000) and DSE (*β* = 0.114, *t* = 2.939, *p* = 0.002) by providing a positive effect of TIGAI on AIEA under the influence of AI Training Exposure (AITE) and on DSE under the influence of TIGAI (AITE), therefore, indicates that formal learning interventions do increase the All these findings support the hypothesis of the model and provide substantial empirical evidence of the relationships that are hypothesized.

Table V
Path analysis

Path	Beta Value	*t* Value	*p*-Value	Decision
TIGAI → CAB	0.574	11.691	0.000	Accepted
TIGAI → PAIIDM	0.439	7.691	0.000	Accepted
TIGAI → DSE → CAB	0.081	3.384	0.000	Accepted
TIGAI → DSE → PAIIDM	0.172	5.562	0.000	Accepted
TIGAI → AIEA → CAB	0.067	2.815	0.005	Accepted
TIGAI → AIEA → PAIIDM	0.095	3.102	0.002	Accepted
AITE × TIGAI → AIEA	0.096	3.416	0.000	Accepted
AITE × TIGAI → DSE	0.114	2.939	0.002	Accepted

Discussion

The findings provide new insights into mutually reinforcing links among trust in generative AI, user capability, ethical orientation, and technology use behaviors. The establishment of all the hypotheses highlights the complexity of trust as a consistent attitudinal construct that influences technology usage through mediating mechanisms (Dang & Li, 2025; Huynh, 2024). The results show that trust in generative AI positively and significantly impacts career advancement behaviors, which supported Hypothesis 1. This result is consistent with the Technology Acceptance Model (TAM), according to which the assessment of perceptions of reliability, fairness, transparency, and safety are the basic elements that influence an attitude and the intention to perform a behavior when the generative AI is perceived as reliable, transparent, and unbiased (Davis, 1989; Sarstedt et al., 2021) such that the inclination to involve the generative AI in the work of forming an individual career development increases when the latter is regarded as reliable, transparent, and unbiased (Liu et al., 2024). According to the Social Cognitive Theory (SCT), the technology trust may be used as an environmental facilitator to enhance confidence and proactive career-related behaviors (Bandura, 2001), such as acquisition of skills, knowledge gain, and engagement in innovative projects (Venkatesh & Davis, 2000). The result aligns with previous empirical research indicating that trust in GenAI is linked to a high degree of receptiveness towards AI professional decision-making and strategic planning, and this factor has a career advancement implication (Bandura, 2001; Huynh, 2024; Solaiman, 2024).

The findings confirm Hypothesis 2, which states that trust in generative AI is a significant predictor of the use of AI-instrumented decision-making by the people. The result is consistent with earlier research that indicates that users become more interested in artificial intelligence-based decision making when the outputs provided by an AI are viewed as fair, unbiased, and transparent (Albashrawi, 2025; Huynh & Aichner, 2025; Solaiman, 2024). The Theory of Planned Behavior (TPB) explains that the more trust an individual has, the greater the favourable attitudes and perceived control, which increases the readiness to incorporate AI into the collaboration decision-making process (Jiao & Cao, 2024; Tian et al., 2023).

The correlation with Hypotheses 3 and 4 supports the hypothesis that digital self-efficacy plays a mediating role in the relationship between trust in generative AI and the career advancement behaviors on the one hand and the role in making AI-informed decisions on the other hand. This mediating effect is in line with Social Cognitive Theory, which has recognized self-efficacy as a key source of translating beliefs into purposeful action (Bandura, 2001). In the event that generative AI is seen to be plausible, just, open, and secure, users will be more empowered to perform it successfully, which also motivates more involvement in career progression and AI-assisted decision-making (Balakrishnan & Dwivedi, 2021; N. A. Khan et al., 2024). This is also associated with the fact that the Technology Acceptance Model, in which trust improves the perceived ease of use and mitigates barriers to continued technology adoption (Jiao & Cao, 2024).

Hypotheses 5 and 6 are also supported, which proves that the relationship between trust in generative AI and either of the two career advancement behaviors is mediated by AI ethical awareness and can be extended to the ethical awareness perspective (Solaiman, 2024) and the Knowledge-Attitude-Behavior (KAB) model. Increased trust promotes deeper, thoughtful, and deliberate interaction with an AI system, and thus enhances ethical consciousness regarding fairness, prejudice, and transparency (Balakrishnan & Dwivedi, 2021; Hughes et al., 2025). The trust in AI does not mean unconditionally relying on AI but helps in using AI outputs by an informed and ethical approach (Dang & Li, 2025; Huynh, 2024). In ethical awareness, the application of skills alone is insufficient in shaping career growth behavior, but a sense of professional values and responsible use of technology also contribute to it (Mendy et al., 2025). Similarly, when making an ethical decision with AI, the

ethical consciousness would operationalize AI suggestions in a manner that is just and accountable (Albashrawi, 2025; Solaiman, 2024). This is consistent with the recent empirical data that demonstrated increased human-AI cooperation and minimization of the risks of overdependence on the biased output is possible due to ethical awareness (Ferhataj et al., 2025).

The evidence in support of Hypotheses 7 and 8 suggests that AI training exposure positively changes the results of trust in generative AI on digital self-efficacy and AI ethical awareness. As per the Knowledge-Attitude-Behavior (KAB) model (Ajzen, 1991), the exposure to AI training reinforces positive attitudes, based on trust, into higher competence and awareness of ethical behavior (Ferhataj et al., 2025). Training equips the mastery experience that improves digital self-efficacy as viewed through the prism of the Social Cognitive Theory (Jiao & Cao, 2024; Liu et al., 2024). On the same note, the exposure training may enhance awareness of the ethical principles of AI, risk of bias, and transparency, thus enhancing the connection between trust and ethical awareness (Bandura, 2001; Jiao & Cao, 2024). Trust, in general, can inspire, and training can provide the cognitive and procedural knowledge that improves the development of skills and their proper use (Liu et al., 2024). The role of training amplification in a dynamic environment where technical expertise and moral literacy are required implies that credibility is based on experience and not appearance (Dai et al., 2025).

Overall, this research indicated that the development of trust towards generative AI is one of the primary areas of foundation of advanced digital capabilities, ethical and responsible conduct, and proactive involvement in AI-infused decision-making. Mediating outcomes of digital self-efficacy and AI ethical awareness show that trust alone cannot work without internal processes that help convert the trust to action (Albashrawi, 2025; N. A. Khan et al., 2024). The mediation effect of AI training exposure also underscores the significance of lifelong learning to create capacity and moral responsibility in using AI (Mendy et al., 2025). Combined, the results provide viable advice to organizations, educators, and policymakers to derive maximum advantages of AI adoption, such as development of trust, adoption of literacy in users, instilling ethical literacy, and establishing sound training paradigms (Dai et al., 2025; Law, 2024; Wang & Kim, 2025). This way, the confidence in generative AI may be utilized as a credible platform of decision support and a career development instrument in a changing digital environment (Huynh, 2024; Solaiman, 2024).

Theoretical implications

Theoretically, the contribution of the current study to the literature is exploring the role of trust in generative AI in working through personal psychological processes to shape technology-related behavior. The research combines Technology Acceptance Model (Davis, 1989; Jiao & Cao, 2024), Social Cognitive Theory (N. A. Khan et al., 2024), and ethical awareness perspective based on the 4-component model of moral behavior proposed by Rest (1986) to create a rather comprehensive framework of the direct and indirect impact between trust and the results of the behaviors. The results verify that trust is perceived as internal cognitive and moral because the digital self-efficacy and AI ethical awareness played the mediating roles (Ibrahim & Aldawsari, 2023; Solaiman, 2024). It is consistent with the earlier studies that emphasized that perceived competence and ethical thinking play a crucial role in the adoption of technology (Jobin et al., 2019). The integration goes beyond theoretical discourse because it reconceptualizes trust as an activating condition in a chain of psychological and behavioral processes in human-AI exchange.

In addition, this research, on a theoretical basis, proved that contextual enablers, i.e., AI training exposure, act as a moderator in trust-based models. As opposed to the previous models, which theorize trust as a comparatively stable attitudinal phenomenon, this paper presented the dynamic aspects of trust that can either empower or discredit the action of trust based on the Knowledge-Attitude-Behavior model (Venkatesh & Davis, 2000) and capability-establishment Social Cognitive Theory (SCT) (Cho & Ofosu-Anim, 2025; N. A. Khan et al., 2024). This extension means that the attitudinal variables are not sufficient to model trust in emerging technologies and factors of development, like training conditioning trust effects. In this regard, the integrated model provides a contextual theoretical explanation of the joint influence of psychological trust and experiential learning on the behavior of adopting AI.

Practical implications

The results of this study are beneficial in practical uses, especially to educational institutions, organizations, and policymakers who aim to use generative AI successfully. Since trust is at the core of AI career development and decision-making actions, the most important strategies that institutions should adopt are those that advance the trustworthiness, fairness, transparency, and safety of the AI systems (Hughes et al., 2025; Huynh, 2024). To begin with, these strategies involve open communication of AI actions, explicit revealing of algorithmic decision-making procedures, and systems enabling users to countercheck AI-produced results (Balakrishnan & Dwivedi, 2021; Hughes et al., 2025). Secondly, the inclusion of AI literacy in educational and professional development courses will contribute to the increased confidence and ethical literacy of users and allow them to make more informed decisions in the technology-saturated environment (Albashrawi, 2025). All these endeavors not only enhance AI adoption, but also a culture of informed trust that leads to long-term acceptance not only in the industry, but also in education as well.

The second important implication is that exposure to AI training has a moderate influence on the association among trust, ethics, and self-efficacy. One way of responding to this observation by organizations and educational institutions are to create specific AI training curricula

that not only focus on the development of technical skills but also on ethical consciousness (Dissanayake & Al-Sharify, 2025; McGuire, 2014). The institutions can maintain the beneficial effects of the trust and improve digital self-efficacy and ethical judgment in AI-related situations by offering easily available, situation-specific, and experiential training (Huynh & Aichner, 2025; Liu et al., 2024). Such interventions could be provided either in workshops, online courses (Boubker, 2024), or joint AI labs, and this ensures that the trust towards AI is converted into practical, ethical, and professionally beneficial practices (Heo, 2025). These initiatives not only equip the labor force to address the demands of integrated work environments but also enhance the organizational ability to make strategic decisions supported by AI.

Limitations of the study

Even though the current study can make valuable contributions to the understanding of the interdependence between the trust in generative, digital self-efficacy, AI ethical awareness, and the related behavioral consequences, one should admit several limitations. To begin with, the research design employed in the study was a cross-sectional design, and it confines the capacity of making causal conclusions between the research variables. Although the proposed relationships are consistent with other known theories, including the Social Cognitive Theory (SCT) and the Knowledge-Attitude-Behavior model, longitudinal data are needed to investigate the temporal sequence and vary the trust-related constructs with time (N. A. Khan et al., 2024; Shaban et al., 2024). Second, the students were used to get their data through self-report measures, thus introducing common method bias and social desirability effects. Even though validated scales have been used in order to minimize errors in measurements, the use of only one source of data might also bring about biases and compromise the generalizability.

The other limitation is the focus on a single population group, which could be limited to other groups. The sample size was sufficient to perform SmartPLS analysis; however, further studies should involve population and occupation diversity in order to examine the generalizability in different cultural, professional, and generational settings. Moreover, the paper operationalized the trust in generative AI in the form of a composite measure of perceived reliability, fairness, transparency, and safety without separating the impact of each dimension. Disaggregated analyses could determine the dissimilar effects of each element of trust on self-efficacy, ethical consciousness, and performance. Besides that, the model failed to include the external contextual factors, including organizational AI policies, regulatory processes, or peer pressure, that can moderate or mediate the relationships involved and form a full picture of AI adoption practices.

Future research direction

Going by the outcome of this research, a longitudinal or experimental design of the research can be used in future studies to determine stronger causal linkages between trust in generative AI, psychological mediators, and behavioral outcomes. Longitudinal analysis of trust, self-efficacy, and ethical awareness may help identify developmental trends and circumstances that can either support or undermine trust over the long-term use of AI (Ferhataj et al., 2025). The strength of a trust-capability-behavior relationship could also be evaluated experimentally by evaluating the effects of specialized learning experiences through experimental interventions like controlled AI training programs. In addition, the emotional response to AI, including anxiety or enthusiasm, and the measure of how the latter influences the former influence the adoption behavior may be studied in the future as well (Huynh & Aichner, 2025; Liu et al., 2024; Tian et al., 2023; Wang & Kim, 2025).

By looking at more groups of users, e.g., working professionals, AI programmers and developers, or policymakers, the level of generalizability might be increased. The cross-cultural research may also result in some comparative information on the impact of cultural values and risk attitude as well as the social norms on the development of trust in generative AI and its behavioral consequences (Kamila & Jasrotia, 2025). It is also possible that in the future, contextual moderators are included, such as organizational AI governance policy, previous experience of AI failure, and peer pressure on the adoption decision-making (Liu et al., 2024). Both individual and institutional levels of trust might be analyzed on a multi-level to develop more detailed descriptions of user engagement in AI-based decision-making and career development (Tian et al., 2023). Lastly, subdivision of trust into dimensions can provide more accurate theoretical information and better support of actual practice.

Conclusion

This study demonstrates that trust plays a central role in generative AI, directly and indirectly fostering career development behaviors and AI-integrated decision-making through digital self-efficacy and AI ethical awareness. By integrating Social Cognitive Theory (SCT), Technology Acceptance Model (TAM), and Knowledge-Attitude-Behavior perspectives, this study develops a comprehensive framework linking psychological trust, internal capability building, ethical awareness, and behavioural participants. The findings further indicate that trust is not a passive belief but an active facilitator operating through cognitive and moral pathways, with its effects amplified by AI training exposure. These results contribute to the theory and practice by emphasizing that the successful implementation of AI into the learning and working setting depends on trust development, user competence building, and the advancement of ethical awareness. The study also highlights that such strategic interventions as focused training and open AI governance are most likely to increase the benefits of AI adoption. Even though the study is confined by factors such as cross-sectional design and population specificity, it leaves open the possibilities of having longitudinal, cross-cultural, and experimental

studies into perspective and broadens the applicability to extend and refine these findings in the future. Overall, the study confirms that dynamic interactions among trust, capability, ethics, and contextual support underlie the sustainable and responsible use of generative AI, providing a foundation for future research and policy development.

Declaration Statement

Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Author contributions

All authors significantly contributed to the various section of the study's conception and design, including, Conceptualization (U.Z.; M.A.; B.Z.), Methodology (U.Z.; S.R.), Data Collection (M.A.; B.Z., S.R.), Analysis and Interpretation (M.A.; B.Z., U.Z.), Writing – Original Draft (U.Z.; M.A.; B.Z., S.R.) and Writing – Review & Editing (U.Z.; M.A.; B.Z., S.R.). All authors have read and approved the final manuscript.

Informed consent

Informed consent was obtained from all individual participants included in the study. Participation was voluntary, and confidentiality of responses was ensured.

Use of generative AI

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Appendix

Trust in Generative AI

Perceived reliability of GenAI

1. In my opinion, generative AI generates valid and reliable results.
2. Generative AI can be trusted with enhancing the quality of work.
3. The results of generative AI are satisfactory to me.

Perceived fairness and non-bias of GenAI

1. In my opinion, generative AI is not biased in decision-making.
2. Generative AI is unbiased to any type of input and user.

Transparency of GenAI output(2 items)

1. Generative AI is easy to understand its decision-making process.
2. I can find enough data on the process of generative AI production of its products.

Perceived safety in using GenAI(3 items)

1. I am sure that there will be no harm to my work or data when I use generative AI.
2. In my opinion, generative AI aims to safeguard the privacy and security of users.
3. The generative AI systems that I consume are designed keeping the safety of users in

Career Advancement Behaviors

1. I am not hesitant to engage in using AI tools to improve my working abilities.
2. I apply generative AI to enhance the level of my work outputs.
3. I also show initiative to acquire new skills in AI which can be useful to my career.
4. My performance on my academic or professional tasks is highly improved with the use of AI-generated insights.
5. To remain competitive in my sphere, I use AI applications in my work.

Participation in AI-integrated decision-making

1. I actively engage in decision-making activities that entail the use of generative AI tools.
2. I am confident in sharing my views within the AI-assisted decision-making situation.
3. I often participate in debates concerning AI-driven suggestions.
4. I also participate in the assessment of the results of AI-based decisions.

Digital self-efficacy

1. I have no doubts that I will be able to apply generative AI successfully.
2. I am able to debug issues with the help of generative AI.
3. I will be able to self-educate about new AI features.
4. I will not find it challenging to adjust to AI technologies changes.
5. I can convey AIs-related ideas to other people.
6. I will be able to use the appropriate AI tool in various tasks.

AI ethical awareness

1. I am aware of the moral concerns connected to utilization of generative AI.
2. I have heard about the dangers of biasness in AI systems.
3. Before applying AI in making decisions, I take into account the social implications of the technology.
4. In my opinion, the responsible usage of AI systems should be made.
5. I am familiar with the necessity of transparency of AI algorithms.

AI training exposure

1. I have been provided with the formal training on how to use generative AI.
2. I have been attending AI ethics workshops or courses.
3. I have been involved in practical practice with AI tools.