International Journal of Multidisciplinary Research of Higher Education (IJMURHICA)
http://ijmurhica.ppj.unp.ac.id/index.php/ijmurhica

The Mediating Role of Trust in Generation Z's Intention to Use Artificial Intelligence-Based Career Preparation Systems

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Article Information:
Received February 4, 2026
Revised March 5, 2026
Accepted April 26, 2026

Keywords: *UTAUT, information quality, artificial intellegence, career preparation, trust*

Abstract

Understanding the determinants of Generation Z's sustained use of Artificial Intelligence-based career assistance is essential, as this cohort increasingly relies on Artificial Intelligence technologies to make high-stakes career decisions. The research examines how information quality shapes performance expectancy and trust, and how performance expectancy, effort expectancy, social influence, facilitating conditions, and trust influence the intention to continue using Artificial Intelligence-based career tools. A quantitative explanatory design with exploratory elements was employed. Data were collected via an online questionnaire distributed to Generation Z individuals who have used Artificial Intelligence for career-related activities, yielding 213 valid respondents. The data were analyzed using PLS-SEM. The findings reveal that information quality significantly enhances both performance expectancy and trust. Performance expectancy, social influence, and facilitating conditions had significant positive effects on the intention to continue using Artificial Intelligence for career preparation. Trust also demonstrated a crucial mediating role in reinforcing continued usage intention. Meanwhile, effort expectancy did not significantly affect intention to continue. Overall, the results highlight the importance of delivering accurate, relevant, and reliable Artificial Intelligence-generated information and building user trust to support sustained Artificial Intelligence adoption among Generation Z.

INTRODUCTION

Artificial Intelligence has transformed many aspects of life, including career planning and preparation. Generative Artificial Intelligence tools such as ChatGPT, Google Gemini, Deepseek, etc. are now popular tools. increasingly used for resume writing, interview simulations, and personalized career guidance. In a complex and competitive job market, Artificial Intelligence offers meaningful support especially for Generation Z (Gen Z), the most digitally native cohort (Bankins et al., 2024). Generation Z, born between 1997 and 2012, has a high level of technology adoption. According to a survey by APJII, (2025), the adoption rate of Artificial Intelligence technology in Indonesia is dominated

How to cite: Kamil, C., Roostika, R. (2026). The Mediating Role of Trust in Generation Z's Intention to Use Artificial Intelligence-Based Career Preparation Systems. *International Journal of Multidisciplinary of Higher Education (IJMURHICA)*, *9*(2), 583-598.

E-ISSN: 2622-741x
Published by: Islamic Studies and Development Center Universitas Negeri Padang

by Generation Z, with a user percentage of 43.7%, far higher than millennials (22.3%), Gen X (12.8%), and baby boomers (8.9%). Meanwhile, in the workplace, a report by Microsoft & LinkedIn (2024) note that 92% of Indonesian office workers have used Artificial Intelligence to enhance productivity. These findings indicate that Indonesian Gen Z, as digital natives, holds strong potential to be the most active adopters of Artificial Intelligence, particularly in career preparation contexts.

According to Camilleri, (2024), Artificial Intelligence usage depends on individuals' perceptions of information quality and trust, influenced by performance expectancy, effort expectancy, social influence, and facilitating conditions. According to Wang, (1996), information quality is important because Artificial Intelligence provides answers based on data collected and trained. However, many believe that Artificial Intelligence-generated answers are not always accurate or relevant and can even cause hallucinations or bias (Lim et al., 2025). Information quality refers to the extent to which an information system provides accurate, relevant, timely, and reliable information (DeLone & McLean, 1992). For Gen Z users of Artificial Intelligence tools, information quality reflects how well Artificial Intelligence responses meet their needs, such as creating CVs, answering interview questions, or offering career guidance. Previous research by Camilleri, (2024) shows that high information quality significantly enhances performance expectancy and trust by reinforcing perceptions of usefulness.

According to Venkatesh et al., (2003), the Unified Theory of Acceptance and Use of Technology (UTAUT) model explains technology adoption through four key constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions. In this study, UTAUT functions as a mediator linking perceptions of information quality to trust, which then shapes continuance intention in using Artificial Intelligence for career preparation. Within UTAUT, performance expectancy is the strongest predictor of technology use, reflecting beliefs that AI can enhance user performance. Prior studies confirm that performance expectancy most strongly drives continued use intention (Bankins et al., 2024; Chau et al., 2025; Y. Li & Wang, 2021). For Gen Z, who are efficiency driven perceived career benefits of Artificial Intelligence increase their likelihood of ongoing use. When Artificial Intelligence provides accurate, relevant, and useful career information, it strengthens performance perceptions, builds trust, and reinforces continued usage intention.

Previous research, there appears to be an inconsistency in findings related to factors that influence the adoption and continued use of Artificial Intelligence technology. Research by Camilleri, (2024); Jung et al., (2025), show that all variables in the tested model, including information quality and trust, have a significant effect on usage intention. However, (Lim et al., 2025; Zhao et al., 2025) found different results, where performance expectancy, effort expectancy, social influence, and facilitating conditions were not significant. These discrepancies indicate that the UTAUT model is not yet fully consistent in the context of Artificial Intelligence use, particularly among students or Generation Z. Moreover, although information quality and trust have been examined in Artificial Intelligence contexts, few studies investigate their combined effects on sustained intention to use Artificial Intelligence for career preparation. This study addresses that gap by integrating information quality and trust into the UTAUT framework to explain Gen Z's Artificial Intelligence adoption behavior. The novelty lies in this integration and in focusing specifically on Gen Z, digital natives transitioning from education to the workforce with unique technology adoption patterns.

This study adopts and develops the model used by Camilleri, (2024); Lim et al., (2025), which applies the UTAUT framework to explain user behavior in the context of Artificial Intelligence-based technology use. Unlike previous studies, this study develops the model by adding information quality as an external factor that influences the four main constructs of UTAUT. In addition, this study also integrates trust as a mediating variable that bridges the influence of UTAUT constructs on the intention to continue. This study specifically focuses on Generation Z in Indonesia, individuals born between 1995 and 2010 who are actively planning and preparing their careers (Grace-Bridges, 2019). Considering the local context and the digital-native characteristics of Gen Z, this model is expected to provide a more comprehensive understanding of the behavior of adopting Artificial Intelligence technology as a career-preparation assistant. based on figure 1.

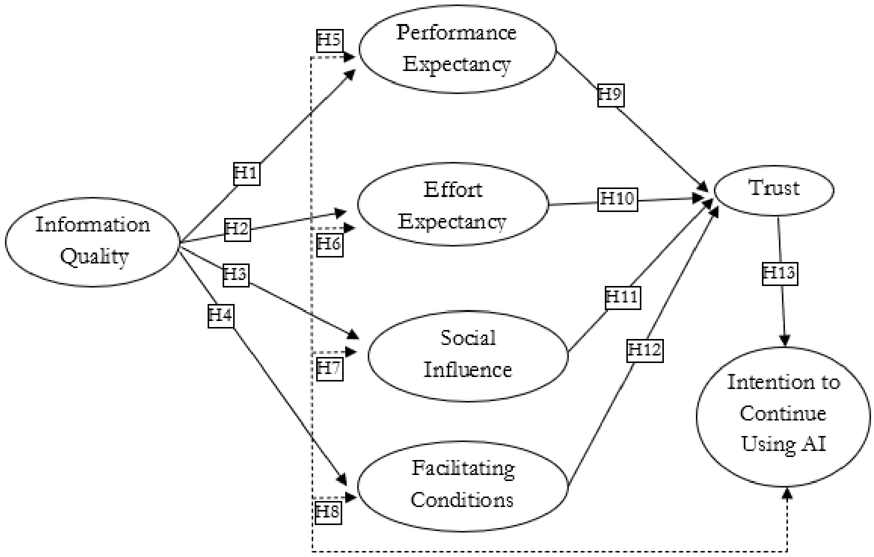

Fig 1. Conceptual Framework

In summary, further investigation is required to deepen our understanding of Generation Z's use of Artificial Intelligence for career preparation. Although the adoption of Artificial Intelligence-based tools continues to grow, the determinants of Gen Z's intention to sustain their use remain insufficiently examined. Existing studies have yet to explore how information quality and trust enhance or interact with core UTAUT constructs namely performance expectancy, effort expectancy, social influence, and facilitating conditions to influence continuance intention. Consequently, the underlying mechanisms that encourage or hinder the long-term use of Artificial Intelligence for career-related purposes remain unclear.

Beyond this theoretical gap, the adoption of Artificial Intelligence for career preparation also carries significant strategic implications for organizations. As Generation Z increasingly enters the workforce, their dependence on Artificial Intelligence-based tools shapes talent readiness, digital skill development, and expectations toward technological support within organizational environments. Understanding these behavioral tendencies is essential for managers and HR leaders, as such insights can guide the design of Artificial Intelligence-enabled talent development initiatives, the enhancement of recruitment and onboarding processes, and the strengthening of organizational digital capabilities. In this way, research in this area contributes not only to technology adoption literature but also to broader discussions on workforce development and strategic organizational planning.

METHODS

This study employs a quantitative research design with an explanatory approach supported by exploratory elements to extend the traditional UTAUT framework by incorporating Information Quality and Trust as external and mediating variables. The research aims to examine how Information Quality, Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, and Trust influence Generation Z's Intention to Continue Using AI-based tools for career preparation. The results are expected to provide empirical evidence on the strength of these relationships and deepen understanding of the behavioral factors that drive continuous AI use among Generation Z.

The research model comprises seven reflective latent variables, each measured by multiple indicators adapted from (Baroud et al., 2025; Busral et al., 2025; Camilleri, 2024; Engkizar et al., 2025; 2018; Iskandar et al., 2023; Jung et al., 2025; Kassymova et al., 2025; Lim et al., 2025; Mutiaramses et al., 2025; Niu & Mvondo, 2024; Putra et al., 2020; Sajja et al., 2025; Venkatesh et al., 2003; Zhao et al., 2025). All indicators were assessed using a six-point Likert scale (1 = strongly disagree; 6 = strongly agree) to improve discriminatory power and reduce neutral responses. A pilot study involving 45 respondents was conducted to ensure reliability and validity prior to the main data collection.

The population includes Generation Z individuals in Indonesia who have used Artificial Intelligence for career preparation, such as CV creation, interview simulations, and career guidance. Due to the dispersed nature of the population, this study uses convenience sampling, a method recommended by (Sekaran & Bougie, 2016), for selecting accessible, willing participants. The sample consists of individuals aged 18–28 with prior experience using generative AI for career-related tasks. Following (J. Hair & Alamer, 2022), a minimum of 5 - 10 respondents per indicator was required. Therefore, the target sample ranged from 135 to 270. This study obtained 213 valid responses. Primary data were collected through an online questionnaire distributed via Google Forms and shared on social media. The survey included an introduction outlining the research purpose, anonymity, and consent, followed by a screening question to verify prior Artificial Intelligence usage. Eligible respondents proceeded to the measurement section, which contained all variable indicators. Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS, chosen for its suitability in predictive and exploratory research, complex models, and mediation testing. The analysis consisted of evaluating the measurement model (reliability and validity) and the structural model (path coefficients, R-square, and effect sizes). Bootstrapping procedures were applied to assess the significance of direct and indirect relationships.

RESULT AND DISCUSSION

Descriptive Analysis of Respondent Profiles

This chapter presents findings on factors that influence the intention to continue using Artificial Intelligence services. The analysis was conducted descriptively and through PLS-SEM statistical testing. Only 213 respondents met the criteria and were eligible for analysis after a screening process based on sample characteristics and the removal of redundant data.

Table 1. The demographic profile of the research participants

Gender	Frequency	Percentage
Famale	121	56.8%
Male	92	43.2%
Age		
>19	10	4.7%
20 – 29	204	95.3%
Typer of Work		
Students	39	18.2%
Government Employment	36	16.8%
Private Employment	59	27.6%
Entrepreneur	44	20.6%
Other	36	16.8%
Domicile		
Bali	12	5.6%
Bandung	29	13.6%
Jakarta	37	17.3%
Kalimantan	11	17.3%
Semarang	22	10.3%
Sulawesi	8	3.7%
Sumatra	13	6.1%
Surabaya	25	11.7%
Yogyakarta	36	16.8%

Based on the demographic summary, the respondents comprised 92 males (43.2%) and 121 females (56.8%) among 213 participants, indicating a female majority. This distribution aligns with prior studies suggesting that technology acceptance may vary across demographic factors, including gender. Regarding age, most respondents were between 20 and 29 years old (204, or 95.3%), with only 10 (4.7%) aged below 20. This dominance of younger users, primarily Gen Z supports the study's relevance, as this group is generally more adaptable to technological developments, such as Artificial Intelligence, for career preparation. The respondents also represented diverse occupational backgrounds. Private-sector employees were the largest group (59 respondents, or 27.6%), followed by entrepreneurs (44 respondents, or 20.6%), students (39 respondents, or 18.2%), and both government employees and other occupations (36 respondents each, or 16.8%). This variation provides a broader perspective on Artificial Intelligence adoption across users with differing professional needs and experiences.

Table 2. The demographic profile of the research participants

Platform	Frequency	Percentage
ChatGPT	121	46,5%
Gemini	105	40,4%
DeepSeek	83	31,9%
Blackbox Artificial Intelligence	66	25,4%
Perplexity	3	1,2%
Grok Artificial Intelligence	1	0,4%
Copilot Artificial Intelligence	1	0,4%
Claude	1	0,4%

Based on table 2 ChatGPT is the most widely used Artificial Intelligence service, with 121 respondents (46.5%). This indicates that ChatGPT is the preferred platform among Gen Z, likely due to its accessibility, broad language capabilities, and versatile career-preparation features. Gemini ranks second among services, with 105 users (40.4%), reflecting its strong appeal for reliable information retrieval and integration within the familiar Google ecosystem. DeepSeek is used by 83 respondents (31.9%), suggesting growing interest in alternative Artificial Intelligence tools for technical writing, academic research, and data analysis. Blackbox Artificial Intelligence, used by 66 respondents (25.4%), appears more relevant for users with technology or programming backgrounds due to its coding assistance features. Other Artificial Intelligence services, such as Perplexity (1.2%), Grok Artificial Intelligence (0.4%), Copilot Artificial Intelligence (0.4%), and Claude (0.4%), show very low usage, likely due to limited access, lower popularity in Indonesia, or more specialized functions. Overall, these results indicate that Gen Z tends to prefer Artificial Intelligence services that are accessible, widely recognized, and user-friendly, particularly ChatGPT and Gemini, reflecting their emphasis on efficiency, practicality, and technological reliability in academic and career-related activities.

Results of the Measurement Model (Outer Model) Analysis.

The validity test on the measurement model was conducted in two stages, namely by testing the convergent validity and discriminant validity of each construct indicator. The results of the validity test are presented as follows. The results of the convergent validity test are shown in figure 2.

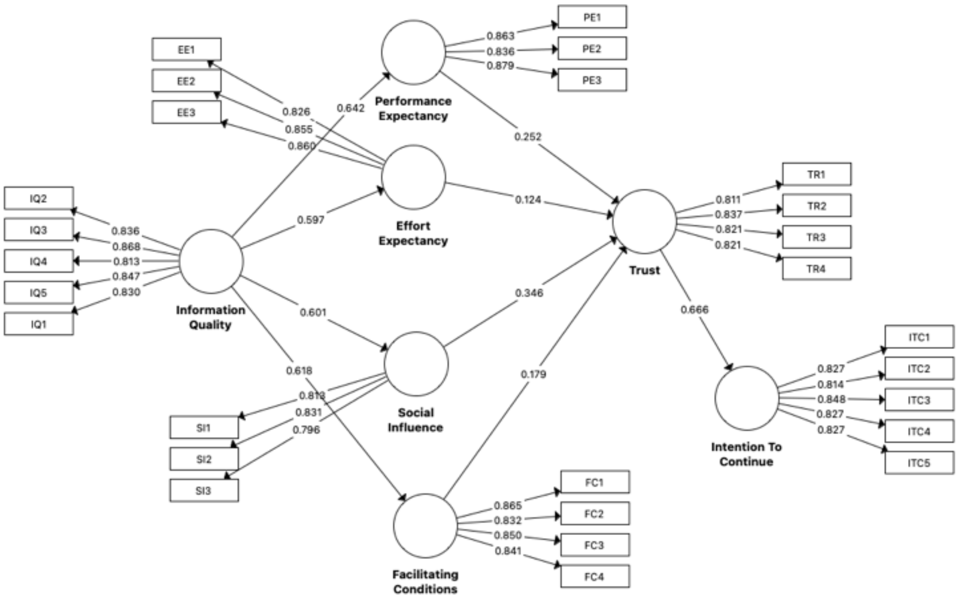

Fig 2. Outer Measurement Model

Based on the convergent validity test using outer loadings, all variables in this study met the required threshold of 0.50, indicating validity according to (Flury et al., 1988). The constructs of Information Quality, Performance Expectancy, and Effort Expectancy consistently showed outer loadings above 0.80, demonstrating strong measurement quality. Social Influence also met the convergent validity criterion, although with relatively lower but still acceptable values above 0.50. Meanwhile, Facilitating Conditions, Trust, and Intention to Continue Using showed high loadings, confirming adequate construct representation. Overall, all constructs satisfied the requirements for convergent validity. The Average Variance Extracted (AVE) values for each construct are presented in table 3.

Table 3. Average Variance Extracted (AVE) Measurement Results

Variable	Average Variance Extracted (AVE)
Information Quality	0.704

Performance Expectancy	0.739
Effort Expectancy	0.717
Social Influence	0.661
Facilitating Conditions	0.718
Trust	0.677
Intention to Continue Using Artificial Intelligence	0.687

Based on table 3 all research variables have AVE values above 0.50, in accordance with the criteria set by Hair et al. (2019). This indicates that each construct explains more than 50% of the variance in the indicators that form it, so it can be said to meet convergent validity. More specifically, the Information Quality variable obtained an AVE value of 0.704, Performance Expectancy of 0.739, and Effort Expectancy of 0.717. All three demonstrate strong validity because their values are well above the minimum limit. The Social Influence variable has an AVE value of 0.661, which, although relatively lower than other variables, still meets the validity criteria. Furthermore, the Facility Conditions variable (AVE = 0.718), Trust (AVE = 0.677), and Intention to Continue Using (AVE = 0.687) also show adequate results. Thus, it can be concluded that all constructs in this study have been measured validly through AVE testing.

Discriminant Validity Test Results

Discriminant validity testing was conducted using the Heterotrait-Monotrait Ratio of Correlations (HTMT) method, and the results are shown in table 4.

Table 4. Results of the Heterotrait-Monotrait Ratio of Correlations (HTMT)

	EE	FC	IQ	ITC	PE	SI	TR
EE							
FC	0.765						
IQ	0.703	0.701					
ITC	0.719	0.720	0.562				
PE	0.788	0.689	0.747	0.662			
SI	0.736	0.797	0.735	0.783	0.749		
TR	0.724	0.732	0.723	0.768	0.765	0.858	

Based on the results of discriminant validity testing using the HTMT method, all correlation values between constructs are below the recommended threshold of <0.90 (Hair et al., 2019). The lowest HTMT value was found between the constructs of information quality and intention to continue using AI, at 0.562, while the highest value appeared in the relationship between trust and social influence, at 0.858. Although 0.858 is the highest value, it remains below the tolerance limit of 0.90, indicating that each construct in this study demonstrates strong discriminant validity. Therefore, all research variables can be empirically distinguished from one another and are appropriate for further structural analysis.

Reliability Test Results

The reliability test in this study uses Cronbach's Alpha and Composite Reliability (CR), with both criteria requiring values greater than 0.6 for the variables to be declared reliable (Ketchen, 2013). The reliability test results for the outer model are presented in table 5.

Table 5. Reliability Test Results

	Cronbach's Alpha	Composite Reliability (CR)
Information Quality	0.895	0.922
Performance Expectancy	0.823	0.895
Effort Expectancy	0.803	0.884
Social Influence	0.744	0.854
Facilitating Conditions	0.869	0.911
Trust	0.841	0.893
Intention to Continue	0.886	0.916

Based on table 5, the results of discriminant validity testing using the HTMT method, all correlation values between constructs are below the recommended threshold of <0.90 (Hair et al., 2019). The lowest HTMT value was found between the constructs of information quality and intention to continue using AI, at 0.562, while the highest value appeared in the relationship between trust and social influence, at 0.858. Although 0.858 is the highest value, it remains below the tolerance limit of 0.90, indicating that each construct in this study demonstrates strong discriminant validity. Therefore, all research variables can be empirically distinguished from one another and are appropriate for further structural analysis.

Structural Model Testing (Inner Model)

In this study, structural model evaluation was conducted using collinearity tests, path coefficient tests, determination coefficients, and Q-square values. The bootstrapping results are shown in table 6.

Table 6. Result of Path Coefficient

	O	T-Statistics	P-Values	Decision
IQ -> PE	0.642	11.303	0.000	Significant
IQ -> EE	0.597	8.178	0.000	Significant
IQ -> SI	0.601	9.765	0.000	Significant
IQ -> FC	0.618	10.688	0.000	Significant
PE -> TR	0.252	3.902	0.000	Significant
EE -> TR	0.124	1.449	0.148	Not Significant
SI -> TR	0.346	5.731	0.000	Significant
FC -> TR	0.179	2.428	0.015	Significant
TR -> ITC	0.666	8.415	0.000	Significant

The results of the path coefficient analysis indicate the direction and strength of the relationships among variables via the β values, which range from 1 to +1. Hypothesis testing is evaluated using the T-statistic and P-value, where a hypothesis is supported when the T-statistic >1.96 and the P-value is <0.05. The detailed results of the hypothesis testing are presented in Table 6. The hypothesis testing results show that Information Quality (IQ) has a positive and significant effect on Performance Expectancy (PE) (T = 11.303, P = 0.000), Effort Expectancy (EE) (T = 8.178, p = 0.000), Social Influence (SI) (T = 9.765, P = 0.000), and Facilitating Conditions (FC) (T = 10.688, P = 0.000). Performance Expectancy (PE) (T = 3.902, P = 0.000), Social Influence (SI) (T = 5.731, P = 0.000), and Facilitating Conditions (FC) (T = 2.428, P = 0.012) significantly influence Trust (TR), while Effort Expectancy (EE) (T = 1.449, P = 0.148) is not significant. Finally, Trust (TR) positively and significantly affects Intention to Continue Using (ITC) (T = 8.415, P = 0.000). Next, mediation testing was conducted to determine whether the trust variable (TR) serves as a mediator in the relationship between the research variables. The results of the mediation test are presented in the following table.

Table 7. Result of Indirect Effects

	O	T-Statistics	P-Values	Decision
PE -> TR -> ITC	0.168	3.649	0.000	Significant
EE -> TR -> ITC	0,083	1.396	0.163	Not Significant
SI -> TR -> ITC	0.231	4.609	0.000	Significant
FC -> TR -> ITC	0.119	2.186	0.029	Significant

The mediation results indicate that performance expectancy significantly influences intention to continue using Artificial Intelligence through trust (T= 3.649, P= 0.000), showing that perceived usefulness strengthens trust and, in turn, promotes sustained AI use. Effort expectancy, however, does not exhibit a significant indirect effect through trust (T= 1.396, P = 0.163), suggesting that ease of use alone does not build the trust needed for continued usage. Social influence demonstrates a strong and significant mediation effect (T= 4.609, P= 0.000), indicating that social encouragement effectively enhances trust and long-term adoption. Finally, facilitating conditions also show a significant indirect effect through trust (T= 2.186, P= 0.029), confirming that adequate technical support and resources strengthen trust and foster continued Artificial Intelligence use.

Collinearity Test Results

The collinearity test was conducted by examining the Variance Inflation Factor (VIF) value as recommended by (Ketchen, 2013). The test results are presented in table 8 below.

Table 8. Collinearity Test Results

	IQ	PE	EE	SI	TR	FC	ITC
IQ		1.000	1.000	1.000		1.000	
PE					1.985		
EE					2.123		
SI					1.961		
FC					2.158		
TR							1.000
ITC							

Based on table 8, all research constructs have Variance Inflation Factor (VIF) values below the recommended threshold of 5 (Hair et al., 2019). This shows that there is no multicollinearity among the variables. The highest VIF values were found in the facility condition and trust variables (2.158), followed by effort expectancy and trust (2.123) and performance expectancy and trust (1.985). Other variables, including social influence and information quality, also had low VIF values below 2. Trust had a VIF of 1.000, indicating no collinearity within the construct. Therefore, all constructs in this study meet the collinearity requirements and are appropriate for further structural model analysis.

Results of the Coefficient Determination/R Square

The coefficient of determination is measured by the R-square value, which indicates the extent to which the independent variables explain the dependent variable. The test results are shown in table 9.

Table 9. Results of the Coefficient of Determination Test (R-Square)

	R-square	R-square Adjusted
Trust	0.583	0.575
Intention to Continue	0.444	0.441

Based on table 9, the R-square for the trust construct is 0.583, and the adjusted R-square is 0.575. This means that 58.3% of the variance in trust is explained by the model's independent variables. The remaining variance comes from factors outside the study. Hair et al., (2019) categorize this level of explanatory power as moderate to substantial. The construct of intention to continue using has an R-square of 0.444 and an adjusted value of 0.441. Thus, 44.4% of its variance is explained by the predictor variables, reflecting moderate explanatory capability. Overall, these results show that the model explains the trust construct well and provides a moderate explanation for intention to continue using.

Q-Square Test Results

The Q-Square test was conducted to assess the ability of independent variables to predict dependent variables. The Q-Square test results are shown in table 10.

Table 10. Q-Square Test Results

	Q^2 predict
Trust	0.383
Intention to Continue	0.405

Based on table 10, the construct of trust has a Q^2predict value of 0.383, while the construct of intention to continue using has a value of 0.405. According to (Ketchen, 2013), Q^2predict values above 0 indicate predictive relevance, and values approaching 0.35 or higher reflect a strong predictive capability. These results indicate that the independent variables in this study provide good predictive contributions to both constructs. This means that the research model demonstrates not only statistical adequacy but also sufficient predictive relevance.

The results show that information quality has a significant positive effect on performance expectancy in Gen Z's use of Artificial Intelligence for career preparation. High-quality information strengthens users' expectations of AI's ability to improve task outcomes such as CV writing and interview preparation. This supports (Bankins et al., 2024; Menon & Shilpa, 2023) who identify information quality as a key driver of perceived system performance. Accurate and relevant information also enhances perceived usefulness (Choe et al., 2021; S. Li et al., 2025) and fosters satisfaction and continued use (Camilleri, 2024; Huang & Chueh, 2022). Information quality also significantly improves effort expectancy, indicating that clear and accessible information reduces the perceived difficulty of using Artificial Intelligence. This aligns with (Kbaier et al., 2025; S. Li et al., 2025) and supports the UTAUT notion that high information quality contributes to ease of use (Venkatesh et al., 2003). For Gen Z, context-appropriate information further minimizes cognitive effort (Bu et al., 2021; Teng et al., 2022). In addition, information quality significantly enhances social influence by increasing users' confidence in recommending AI to peers. This finding aligns with Changalima et al., (2024) and with Chen et al., (2023), who highlight gendered perceptions but confirm consistent positive response when information is credible. The UTAUT model by (Venkatesh et al., 2003), is reinforced, showing that high-quality information fosters broader adoption among Gen Z (Bankins et al., 2024; M. Wu et al., 2024). Information quality also strengthens facilitating conditions by improving users' perceptions of adequate technical support and resource readiness (Bu et al., 2021; Menon & Shilpa, 2023), consistent with (Niu & Mvondo, 2024; Zhao et al., 2025). These findings reflect UTAUT's conceptualization that sufficient resources elevate confidence in using Artificial Intelligence (Li et al., 2025; Terblanche & Kidd, 2022).

Performance expectancy significantly increases trust, indicating that users rely more on AI when they believe it enhances efficiency and accuracy. This aligns with (Camilleri & Falzon, 2021; Jung et al., 2025), and is consistent with UTAUT's assertion that perceived usefulness strengthens security perceptions. In contrast, effort expectancy does not significantly affect trust. Although previous studies found otherwise (Denovan & Marsasi, 2025; Kim et al., 2025), Gen Z's familiarity with technology may reduce the relevance of ease of use (Bankins et al., 2024). Instead, information credibility and system transparency emerge as stronger trust drivers (Sharma et al., 2025; X. Wu et al., 2025). Social influence positively affects trust, underscoring the role of peer recommendations, digital communities, and public figures in shaping Gen Z's confidence in Artificial Intelligence (Bankins et al., 2024; X. Wu et al., 2025; Zhao et al., 2025). Facilitating conditions also significantly enhance trust, indicating that accessible infrastructure and technical support increase perceptions of system reliability (Huang & Chueh, 2022; Y. Li & Wang, 2021; Menon & Shilpa, 2023; Tanantong & Wongras, 2024). Trust significantly increases continuance intention, confirming its central role in long-term digital technology use (Winarno & Roostika, 2024). Gen Z is more likely to continue using Artificial Intelligence when the system is reliable, accurate, and ethically operated (Bankins et al., 2024; Huang & Chueh, 2022; Joshi, 2025).

Performance expectancy also significantly predicts continuance intention, supporting earlier studies (Chau et al., 2025; Kavitha & Joshith, 2024; Lim et al., 2025; Zhao et al., 2025). For Gen Z, intention persists when AI delivers tangible outcomes that support career development. Effort expectancy does not influence continuance intention. For digitally mature users, ease of use is a baseline expectation (Joshi, 2025; Pillai et al., 2024; Teng et al., 2022). Thus not a decisive factor. Social influence, however, significantly increases continuance intention, emphasizing the role of social endorsement and digital community dynamics (Jung et al., 2025; Lim et al., 2025; Rana et al., 2024; Yaqub et al., 2024). Facilitating conditions likewise positively affect continued use, highlighting the importance of infrastructure, stable access, and supportive environments (Chatterjee et al., 2023; Kavitha & Joshith, 2024; Y. Li & Wang, 2021; Sharma et al., 2025).

CONCLUSION

This study shows that integrating information quality and trust into the UTAUT framework provides a clearer explanation of Generation Z's continued use of Artificial Intelligence for career preparation. The findings reveal that information quality significantly strengthens all UTAUT constructs and is central in shaping trust, while performance expectancy and trust emerge as the strongest predictors of continuance intention. These results highlight a new insight that reliable, accurate, and relevant Artificial Intelligence-generated information combined with positive perceptions of usefulness, supportive environments, and social influence collectively drives sustained Artificial Intelligence adoption. The study offers theoretical contributions by extending UTAUT with trust in an underexplored context and linking Artificial Intelligence adoption behavior with employability and human resource development. Practically, the results guide organizations, educational institutions, and SMEs to invest in trustworthy Artificial Intelligence tools, enhance Artificial Intelligence literacy, and design digital strategies that align with Gen Z's technology adoption patterns, ultimately supporting productivity, capability building, and innovation. Although limited by self-reported data, Gen Z's exclusive focus, and a cross-sectional design, the study provides a foundation for future research to include broader samples, longitudinal approaches, and additional variables such as perceived risk, attitudes, and ethical concerns to deepen understanding of long-term Artificial Intelligence adoption.

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International Journal of Multidisciplinary of Higher Education (IJMURHICA)

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