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Factors Influencing Generation Z's Attitude Towards Artificial Intelligence—A Perspective Based on Diffusion of Innovations Theory

Gang Wang [1], Rosidah Binti Musa[2]

[1,2] Faculty of Business Management, City University Malaysia

Abstract

This study, based on the Diffusion of Innovations (DOI) Theory and the Technology Acceptance Model (TAM), explores the key factors influencing Generation Z's attitude towards artificial intelligence. The hypotheses were tested using Structural Equation Modeling (SEM), and the results indicate that perceived usefulness (PU) and perceived ease of use (PEOU) play significant mediating roles between relative advantage (RA), compatibility (COMP), trialability (TRIAL), and complexity (COMPX) and attitude towards use (ATT). Specifically, RA and TRIAL indirectly affect the attitude towards use through PU, while COMP and COMPX indirectly affect the attitude towards use through PEOU. This study not only enriches the application of DOI and TAM but also provides practical suggestions for enterprises in promoting AI products.

Keywords: *Generation Z, Artificial Intelligence, Diffusion of Innovations Theory, Technology Acceptance Model, Structural Equation Modeling.*

1. Introduction

In recent years, the development and application of artificial intelligence (AI) technology have been rapid, widely permeating various fields of society. From intelligent assistants and smart homes to healthcare and autonomous driving, AI is reshaping our lives and work (Dwivedi et al., 2021). As a generation that has grown up with the internet and digital technology, Generation Z is not only the primary user of AI technology but also the key driver of its future application and development (Ameen et al., 2023; Elif Karakoylu et al., 2020). Therefore, studying Generation Z's attitude towards AI technology and its influencing factors is of great significance. However, existing research is still insufficient in revealing the deep mechanisms affecting Generation Z's acceptance of AI technology, particularly in the literature that combines the Diffusion of Innovations Theory and the Technology Acceptance Model in the study of AI technology attitudes.

The Technology Acceptance Model (TAM) proposes that perceived usefulness (PU) and perceived ease of use (PEOU) are the core factors determining users' intention to accept technology (Davis et al., 1989). This model has been widely applied in the study of acceptance of various new technologies (King & He, 2006). However, the TAM model, when explaining

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user behavior, is relatively independent of the characteristics of the technology itself, lacking a systematic consideration of the technical features. In contrast, the Diffusion of Innovations (DOI) Theory provides a detailed description of the technical characteristics and diffusion process through dimensions such as relative advantage (RA), compatibility (COMP), trialability (TRIAL), and complexity (COMPX) (Almaiah et al., 2022). Therefore, combining TAM and DOI can more comprehensively reveal the multiple factors and mechanisms influencing Generation Z's attitude towards AI technology.

This study aims to integrate TAM and DOI theories to construct a conceptual theoretical model that explores the factors influencing Generation Z's attitude towards AI technology from the perspective of innovation diffusion. Specifically, this paper considers relative advantage, compatibility, trialability, and complexity as independent variables that affect Generation Z's attitude towards AI technology (dependent variable) through perceived usefulness and perceived ease of use (mediating variables). Through empirical analysis, this paper aims to reveal the direct and indirect effects of these factors on Generation Z's attitude towards AI technology.

The main research questions of this study include: First, how do perceived usefulness and perceived ease of use affect Generation Z's attitude towards AI technology? Second, how do relative advantage, compatibility, trialability, and complexity influence Generation Z's attitude towards AI technology through perceived usefulness and perceived ease of use? Third, do perceived usefulness and perceived ease of use play a mediating role in the aforementioned relationships? By addressing these questions, this paper hopes to theoretically enrich the application of TAM and DOI in the study of AI technology acceptance and provide practical guidance for enterprises and policymakers to more effectively promote the adoption of AI technology among Generation Z.

2. Literature Review and Hypothesis Development

2.1. Technology Acceptance Model

The Technology Acceptance Model (TAM), proposed by Davis in 1989, is a classic theoretical model for studying user acceptance and use of new technologies (Davis et al., 1989). The core of the TAM model lies in perceived usefulness (PU) and perceived ease of use (PEOU). Perceived usefulness refers to the degree to which a user believes that using a particular technology will enhance their job performance; perceived ease of use is the degree to which a user believes that using a particular technology is free of effort. Numerous studies have shown that PU and PEOU are important antecedents of users' technology acceptance intentions and usage behaviors. For example, Al-Qaysi et al. (2020) provided a systematic review that better summarized TAM-based social media research and offered important references for future research in social media contexts. Additionally, the TAM model has been widely validated in studies across different technological domains, such as e-commerce, mobile payments, and social media (German Ruiz-Herrera et al., 2023; Yang et al., 2023; Zhang et al., 2023).

However, existing research seldom focuses on the specific mechanisms of PU and PEOU in AI technology acceptance, particularly for Generation Z user groups.

2.2. Diffusion of Innovations Theory

The Diffusion of Innovations (DOI) Theory, proposed by Rogers in 1962, aims to explain how new technologies or innovations spread within a social system (Rogers et al., 2014). DOI theory posits that the diffusion process of innovations is influenced by multiple factors, with technological characteristics being a key factor. Relative advantage (RA) refers to the superiority of the new technology compared to existing technologies; compatibility (COMP) is the consistency of the new technology with users' existing values, experiences, and needs; trialability (TRIAL) refers to the possibility for users to experiment with the new technology before fully adopting it; complexity (COMPX) is the ease or difficulty of understanding and using the new technology. Studies have shown that these technological characteristics influence users' technology acceptance and usage behaviors to varying degrees. For example, Al-Rahmi et al. (2019) proposed a TAM extension model with DOI to study the acceptance of e-learning systems designed to improve students' academic performance. However, despite DOI's theoretical advantages in explaining technology diffusion, its application in AI technology research, particularly for Generation Z user groups, remains limited.

2.3. Perceived Usefulness and Perceived Ease of Use

Perceived usefulness and perceived ease of use are the core constructs of the TAM model, which have been widely used to explain users' technology acceptance behaviors. The model specifically states that PU significantly positively affects users' attitudes towards use, while PEOU not only directly influences usage intentions but also indirectly affects usage intentions through PU. In AI technology acceptance research, PU and PEOU have also been shown to be key factors. Studies indicate that when users believe AI technology can enhance their work or life efficiency, they are more inclined to accept and use the technology; simultaneously, if users find AI technology easy to use, they are more likely to accept it (Almaiah et al., 2022). Therefore, based on existing research, we propose the following hypotheses:

H1: Perceived usefulness significantly positively affects Generation Z's attitude towards AI technology.

H2: Perceived ease of use significantly positively affects Generation Z's attitude towards AI technology.

2.4. Relative Advantage

Relative advantage refers to the superiority of new technology compared to existing technology in terms of performance, efficiency, or other aspects. Rogers (2014) points out that RA is one of the main driving forces for users to accept new technology. PU in the TAM model, to some extent, reflects users' perception of the relative advantage of technology. Therefore, we propose the following hypothesis:

H3: Relative advantage significantly positively affects Generation Z's perceived usefulness of AI technology.

2.5. Compatibility

Compatibility refers to the consistency of new technology with users' existing values, experiences, and needs. Studies have shown that highly compatible technologies are more easily accepted by users. In the field of AI technology, users are more likely to perceive ease of use and usefulness when they believe the technology aligns with their daily needs and habits. Therefore, we propose the following hypothesis:

H4: Compatibility significantly positively affects Generation Z's perceived ease of use of AI technology.

2.6. Trialability

Trialability refers to the possibility for users to experiment with new technology before fully adopting it. High trialability helps users reduce perceived risk associated with new technology, enhancing their acceptance intentions. In AI technology applications, allowing users to try out the technology first helps boost their confidence and acceptance of the technology. Therefore, we propose the following hypotheses:

H5a: Trialability significantly positively affects Generation Z's perceived usefulness of AI technology.

H5b: Trialability significantly positively affects Generation Z's perceived ease of use of AI technology.

2.7. Complexity

Complexity refers to the ease or difficulty of understanding and using new technology. Technologies with high complexity typically increase users' cognitive burden and reduce their acceptance intentions. For AI technology, highly complex technologies may confuse and deter users, thus affecting their acceptance. Therefore, we propose the following hypothesis:

H6: Complexity significantly negatively affects Generation Z's perceived ease of use of AI technology.

By integrating the aforementioned theories and hypotheses, this study constructs a new conceptual model (as shown in Figure 1) to reveal the factors influencing Generation Z's attitude towards AI technology and their mechanisms of action from the perspective of innovation diffusion.

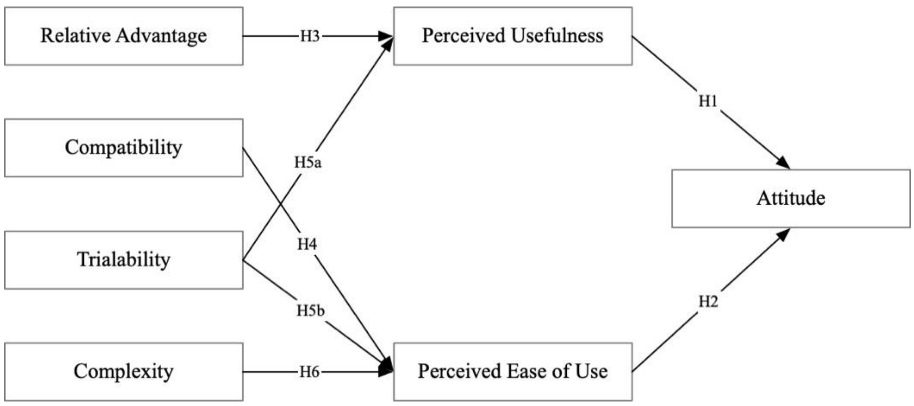

Figure 1: Research model.

Source: Developed for this research

3. Methods

3.1. Data Collection and Sampling

To ensure the broadness and representativeness of the research sample, this study adopted a random sampling method. Respondents were invited to participate in the survey by scanning a questionnaire QR code through online and offline channels. The questionnaire effectively collected data from Generation Z respondents with diverse backgrounds in Shijiazhuang, Hebei Province, China. Subsequently, we cleaned and preprocessed the collected data to eliminate outliers and invalid samples, ensuring the accuracy and reliability of the data.

Referring to Hair et al.'s (2014) recommendations, the sample size should be at least ten times the number of observed items (21 items). This study collected a total of 225 valid samples, meeting the sample size requirements for PLS-SEM analysis. The demographic characteristics of the respondents are detailed in Table 1.

Table 1: Sociodemographic information.

Variables	Frequency	Percent
Gender		
Male	102	45.33
Female	123	54.67
Age		
15-18 years	26	11.56
18-21 years	48	21.33
21-24 years	82	36.44
24-29years	69	30.67
Education		
Undergraduate	67	29.78
Postgraduate	12	5.33
Others	146	64.89

Source: Developed for this research.

3.2. Measurement Structure

The questionnaire design employed a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree), to measure the degree of agreement. All variables in the scale were derived from existing research and appropriately modified according to the specific context of this study to ensure the reliability and validity of the measurements. Specifically, the measurement items for technological characteristics such as relative advantage, compatibility, trialability, and complexity were referenced from Al-Rahmi et al. (2019). The measurement items for perceived usefulness and perceived ease of use were primarily referenced from Davis (1989). The questionnaire also included basic demographic information such as age, gender, and educational level to facilitate descriptive statistical analysis of the sample. Table 2 provides details of the latent variables and their corresponding observed variables.

Table 2: Research Scale.

Observable Variables	Measurement Items
RA1	Using AI technology completes tasks more effectively than traditional technologies.
RA2	AI technology is more efficient than existing technologies.
RA3	AI technology provides better outcomes.
COMP1	AI technology is compatible with my lifestyle.
COMP2	AI technology aligns with my values.
COMP3	AI technology meets my needs.
TRIAL1	I can try AI technology before formally using it.
TRIAL2	I have the opportunity to test AI technology before deciding to use it.

TRIAL3	I can experience AI technology before fully adopting it.
COMPX1	Learning to use AI technology is difficult.
COMPX2	Using AI technology requires a lot of time to learn.
COMPX3	Operating AI technology is complex.
PU1	Using AI technology can improve my work/study efficiency.
PU2	Using AI technology can enhance my productivity.
PU3	Using AI technology is helpful for my work/study.
PEOU1	I find AI technology easy to use.
PEOU2	I find learning to use AI technology easy.
PEOU3	I find AI technology intuitive to operate.
ATT1	I have a positive attitude towards using AI technology.
ATT2	I think using AI technology is a good idea.
ATT3	I enjoy using AI technology.

Source: Developed for this research.

3.3. Data Analysis Methods

This study employed Partial Least Squares Structural Equation Modeling (PLS-SEM) as the primary data analysis tool. PLS-SEM is suitable for predictive research and is advantageous when the research model is complex and includes multiple causal relationships (Hair et al., 2017). Initially, we used SmartPLS 4.0 software for data analysis. The data analysis process was divided into two steps: the first step was the assessment of the measurement model, including the evaluation of reliability and validity; the second step was the assessment of the structural model, including the analysis of path coefficients, explained variance, and predictive relevance.

4. Results

4.1. Measurement Model Assessment

4.1.1. Reliability and Convergent Validity

In the evaluation of the measurement model, reliability and convergent validity are two critical assessment indicators. This study assessed the reliability and convergent validity of the measurement model by calculating Cronbach's Alpha, Composite Reliability (CR), Average Variance Extracted (AVE), and Outer Loadings (Henseler et al., 2015; Lohmöller, 1989; Rigdon, 2012).

As shown in Table 3, the reliability analysis indicates that the Cronbach's Alpha values for all constructs exceed 0.7, demonstrating good internal consistency of the measurement items. CR is used to assess the overall reliability of the measurement model, and all constructs have composite reliability values exceeding 0.8, further confirming the reliability of the measurement model. Convergent validity is assessed by AVE, which reflects the proportion of variance explained by each construct. All constructs have AVE values exceeding 0.5, indicating good convergent validity.

Additionally, Outer Loadings are another important indicator for evaluating convergent validity. As shown in Table 3, all measurement items have Outer Loadings values exceeding 0.7, further verifying the high explanatory power of the items and indicating a strong association between the items and their corresponding constructs. Finally, the Variance Inflation Factor (VIF) is used to assess multicollinearity issues. The VIF values in Table 3 are all below 3, indicating no severe multicollinearity issues in the model (Hair et al., 2017).

Table 3: The evaluation of the measurement model (reliability, validity, and VIF).

Iteams	Loading	Cronbach's alpha	CR	AVE	VIF
RA1	0.810				1.531
RA2	0.856	0.796	0.881	0.711	1.820
RA3	0.862				1.843
COMP1	0.835				1.801
COMP2	0.854	0.806	0.885	0.720	1.820
COMP3	0.856				1.650
TRIAL1	0.808				1.576
TRIAL2	0.883	0.793	0.879	0.708	2.030
TRIAL3	0.831				1.676
COMPX1	0.849				1.728
COMPX2	0.845	0.770	0.867	0.685	1.716
COMPX3	0.789				1.414
PU1	0.847				1.713
PU2	0.855	0.798	0.881	0.713	1.794
PU3	0.830				1.628
PEOU1	0.838				1.521
PEOU2	0.826	0.774	0.869	0.688	1.621
PEOU3	0.824				1.651
ATT1	0.840				1.602
ATT2	0.818	0.788	0.876	0.702	1.609
ATT3	0.855				1.802

Source: Developed for this research.

4.1.2. Discriminant Validity

In the evaluation of the measurement model, discriminant validity is a key indicator to ensure that constructs are independent of each other and that measurement items accurately reflect their respective constructs. This study used the Fornell-Larcker criterion to test discriminant validity, as shown in Table 4.

According to the Fornell-Larcker criterion, the square root of a construct's AVE should be greater than the correlation coefficient between that construct and other constructs (Hamid et al., 2017). The diagonal elements in Table 4 represent the square roots of the AVE for each construct, while the off-diagonal elements represent the correlation coefficients between constructs. The square roots of the AVE for all constructs are greater than their correlations with other constructs, indicating good discriminant validity for the measurement model in this study.

Table 4: Discriminant Validity (Fornell-Larcker Criterion).

	ATT	COMP	COMPX	PEOU	PU	RA	TRIAL
ATT	0.838						
COMP	0.634	0.848					
COMPX	-0.680	-0.703	0.828				
PEOU	0.750	0.651	-0.699	0.829			
PU	0.779	0.624	-0.683	0.731	0.844		
RA	0.727	0.684	-0.724	0.655	0.721	0.843	
TRIAL	0.731	0.693	-0.710	0.696	0.753	0.751	0.841

Source: Developed for this research.

4.1.3. Evaluation of the Model's Explanatory and Predictive Power

In PLS-SEM, the effect level (R^2) and the predictive level (Q^2) of the structural model are very important. Generally, an R^2 value exceeding 0.26 indicates good explanatory power, a value exceeding 0.13 indicates moderate explanatory power, and a value below 0.02 indicates weak explanatory power (Gong et al., 2022). Additionally, the predictive ability of the structural model is evaluated using the blindfolding method in PLS, where a Q^2 value greater than 0 indicates predictive relevance (Gong et al., 2022). Finally, this study examines the explanatory and predictive power of the structural model, with the relevant results detailed in Table 5.

Table 5: Explanatory and predictive properties of the model.

	R^2	R^2 adjusted	SSO	SSE	Q^2 (=1-SSE/SSO)
PU	0.622	0.619	675	385	0.430
PEOU	0.584	0.578	675	413	0.389
ATT	0.677	0.674	675	359	0.468

Source: Developed for this research.

4.2. Structural Model and Hypothesis Testing

The results of the structural model assessment are shown in Table 6, evaluating the significance of each path through the path coefficient (Std β), t-value, and p-value.

Hypotheses H1 and H2 are supported, indicating that perceived usefulness and perceived ease of use significantly positively affect Generation Z's attitude towards using AI technology (β=0.496, P<0.001; β=0.388, P<0.001). Hypotheses H3, H4, H5, and H6 are also supported, indicating that relative advantage, compatibility, and trialability significantly positively affect perceived usefulness and perceived ease of use (β=0.356, P<0.001; β=0.190, P<0.001; β=0.485, P<0.001; β=0.328, P<0.001). Hypothesis H7 is partially supported, as complexity significantly negatively affects perceived ease of use (β=-0.332, P<0.001).

Table 6: Structural Model (p-values) and Hypothesis Testing.

HN	Hypothesized paths	Std β	t values	P values	Results
H1	PU→ATT	0.496	7.889	0.000	Supported
H2	PEOU→ATT	0.388	6.332	0.000	Supported
H3	RA→PU	0.356	4.398	0.000	Supported
H4	COMP→PEOU	0.190	2.506	0.012	Supported
H5a	TRIAL→PU	0.485	5.727	0.000	Supported
H5b	TRIAL→PEOU	0.328	3.827	0.000	Supported
H6	COMPX→PEOU	-0.332	4.220	0.000	Supported

Source: Developed for this research.

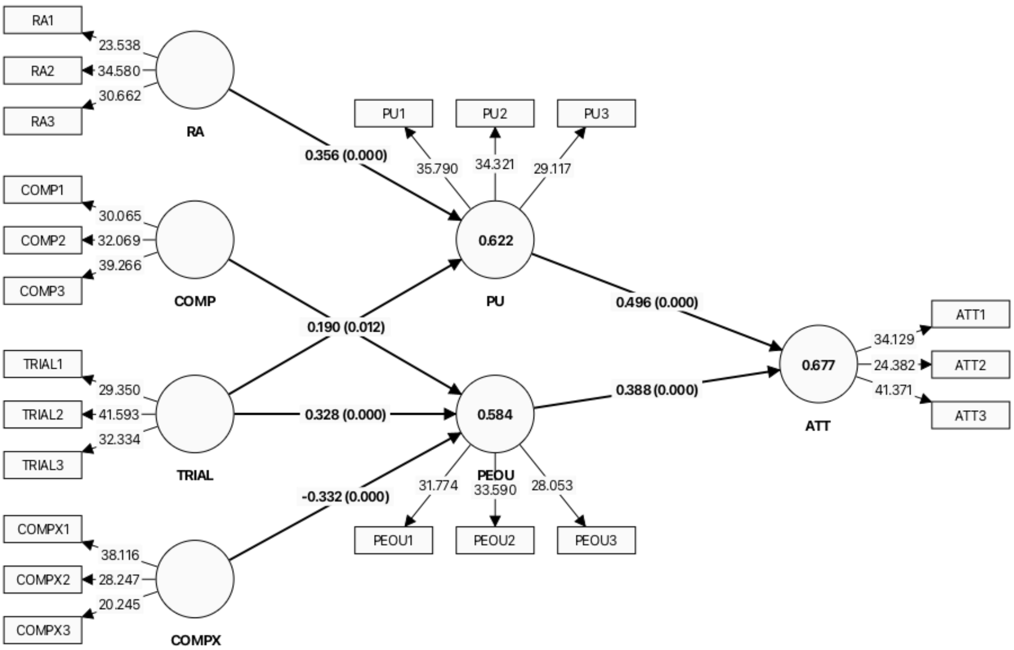

Figure 2: Structural Model and Path Coefficient Results.

Source: Developed for this research.

4.3. Mediation Effect Test

To gain a deeper understanding of the relationships between variables, we conducted a mediation effect analysis to explore the mediating role of perceived usefulness (PU) and perceived ease of use (PEOU) between independent variables and attitude towards use (ATT), as detailed in Table 7. The results show that the path coefficient for the indirect effect of relative advantage (RA) on ATT through PU is 0.176, with a t-value of 3.971 and a p-value of 0.000. The path coefficient for the indirect effect of compatibility (COMP) on ATT through PEOU is 0.074, with a t-value of 2.394 and a p-value of 0.017. The path coefficients for the indirect effects of trialability (TRIAL) on ATT through PU and PEOU are 0.241 (t-value 4.268, p-value 0.000) and 0.127 (t-value 3.056, p-value 0.002), respectively. The path coefficient for the indirect effect of complexity (COMPX) on ATT through PEOU is -0.129, with a t-value of 3.480 and a p-value of 0.001. In summary, PU and PEOU play important mediating roles between relative advantage, compatibility, trialability, complexity, and attitude towards use, further illustrating that users' attitudes towards AI products are not only directly influenced by independent variables but also indirectly shaped through the mediating roles of PU and PEOU.

Table 7: Results of Indirect Effects Testing.

Indirect effects	Std β	t values	P values	Results Support
RA→PU→ATT	0.176	3.971	0.000	Yes
COMP→PEOU→ATT	0.074	2.394	0.017	Yes
TRIAL→PU→ATT	0.241	4.268	0.000	Yes
TRIAL→PEOU→ATT	0.127	3.056	0.002	Yes
COMPX→PEOU→ATT	-0.129	3.480	0.001	Yes

Source: Developed for this research.

5. Discussion and Implications

5.1 Theoretical Contributions

This study integrates the Diffusion of Innovations Theory (DOI) and the Technology Acceptance Model (TAM) to explore the factors influencing Generation Z's attitudes towards AI technology and their mechanisms. The results indicate that perceived usefulness (PU) and perceived ease of use (PEOU) play key mediating roles between technological characteristics and usage attitudes, enriching the theoretical perspectives of existing technology acceptance research. Additionally, this study reveals the significant impacts of relative advantage, compatibility, trialability, and complexity on Generation Z's acceptance of AI technology, providing new directions for future theoretical research.

5.2 Practical Implications

The findings of this study offer important practical implications for companies promoting AI technology. Firstly, companies should focus on enhancing the perceived usefulness and perceived ease of use of AI technology by highlighting its relative advantages and trialability to improve users' positive perceptions. Secondly, companies should consider the compatibility of AI technology with users' existing needs and habits, reduce the complexity of the technology, and improve the user experience. Lastly, companies can increase the adoption rate of AI technology by offering trial and experience activities, allowing users to familiarize themselves with and accept AI technology in a low-risk environment.

5.3 Research Limitations and Future Directions

Despite achieving some results, this study has several limitations. Firstly, the sample is limited to Generation Z users in Shijiazhuang, Hebei Province, China. Future research can consider user groups from different regions and cultural backgrounds to enhance the generalizability of the findings. Secondly, this study collected data through a questionnaire survey. Future research can combine quantitative and qualitative research methods to further explore the specific mechanisms of influencing factors. Lastly, this study primarily focuses on the impact of technological characteristics on usage attitudes. Future research can consider other potential influencing factors, such as social influence and emotional factors, to construct a more comprehensive technology acceptance model.

5.4 Conclusion

Based on the Diffusion of Innovations Theory and the Technology Acceptance Model, this paper explores the key factors influencing Generation Z's attitudes towards AI technology. The empirical analysis reveals that relative advantage, compatibility, trialability, and complexity indirectly affect Generation Z's usage attitudes through perceived usefulness and perceived ease of use. The findings not only enrich the theoretical perspectives of technology acceptance research but also provide strong practical guidance for companies promoting AI technology. Future research can further expand the sample range and combine multiple research methods to deeply investigate the multiple factors influencing technology acceptance.

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