Proceedings of CONF-BPS 2026 Symposium: Sustainability Transitions and Regional Economic Restructuring in New Contexts
DOI: 10.54254/2754-1169/2026.NJ30823

The Impact of Generative AI's Opinion Leader Characteristics on User Adoption of AI-Generated Opinions

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Abstract. Nowadays, GAI has gradually become an important participant in the information seeking and advice provision in people's daily lives. Just like social media as opinion leaders, GAI is also beginning to exhibit the characteristics of an opinion leader. To explore the reasons why users accept AI-generated content, this study draws on the theory of opinion leaders, combining the Technology Acceptance Model and the Integrative Technology Acceptance and Use Theory, and establishes a multi-dimensional research framework, aiming to explore how the opinion leader characteristics of generative AI affect users' usage decisions. Under the influence of three dimensions of users' attitudes towards GAI, the content generation ability of GAI and the platform influence, through three important psychological factors, namely performance expectancy, effort expectancy and social influence, ultimately directly affects users' usage intentions. This study also discovers the moderating effect of personal characteristics. For example, users with high innovative have a higher tolerance for risks; young users are more susceptible to social influence; female users value usability more. At the same time, as users' usage experience increases, the importance of GAI's usability in their decision-making will decrease. By demonstrating the process of users accepting GAI as an opinion leader, this study provides a new theoretical perspective for us to understand the influence in human-computer interaction. It also provides practical suggestions for generative AI platforms to improve user experience and formulate market strategies for different user groups.

Keywords: Generative AI, Opinion Leader, Technology Acceptance Model, UTAUT, User Adoption

1. Introduction

The rapid development of GAI is changing people's daily lives. Take ChatGPT and Deepseek as examples. More and more people are beginning to frequently use them in their daily activities, sharing various matters in life with generative AI and seeking opinions and suggestions. GAI's functions are increasingly approaching those of traditional opinion leaders on social media. However, the way information is generated and provided by generative AI still has significant differences from that of human opinion leaders [1]. The information sources, expression methods, and especially the running algorithm of GAI as a program pose particular challenges in building

DOI: 10.54254/2754-1169/2026.NJ30823

trust relationships. That is, when people turn to GAI as an opinion leader and follow its advice, they are doubt to perceive the risks involved [2].

Currently, through literature research, there have been a large number of studies on social media as opinion leaders, but studies on generative AI as an opinion leader and its acceptance by the public are still relatively few. The seven key differences lie in the different bases of trust: the trust of social media usually comes from traceable content and real social relationships, while trust in generative AI depends more on the accuracy of answers, algorithm transparency, and overall system reliability [3].

Therefore, based on this, this study attempts to explore how the characteristics of generative AI as an opinion leader affect user acceptance from the perspective of opinion leaders. Using the TAM model and UTAUT model, a complete research framework is constructed. This study has several important values: Firstly, the model established in this study includes multiple key variables such as trust, transparency, and personalization, and particularly incorporates perceived risks as an important obstacle for consideration; Secondly, it clarifies the core mediating roles of performance expectations, effort expectations, and social influence, revealing the way generative AI external characteristics affect user intentions; Finally, setting regulatory variables such as users' innovative, age, gender, and usage experience under individual differences, exploring their regulatory effects in different user groups.

By constructing this integrated model, this study can more comprehensively explain various factors affecting the acceptance of generative AI, and will also provide practical theoretical guidance for generative AI platforms, helping them optimize user experience and formulate more effective promotion strategies.

2. Literature review

2.1. Social media and public opinion

Social media opinion leaders play a crucial role in information dissemination. Their influence mainly stems from their professional knowledge, credibility, attractiveness, and the ability to establish deep relationships with the public [4]. The recommendations and viewpoints on social media spread rapidly through social networks, influencing the cognition, attitudes, and even purchasing decisions of their followers. This influence is rooted in people's trust in social media and the widespread recognition of the media platform by various sectors of society [5].

With the rise of GAI, generative AI is increasingly resembling the functions of social media opinion leaders. GAI acts as an information source and advisor by generating high-quality content [6]. GAI mimics the interactive characteristics unique to opinion leaders through a special form of conversation-based opinion provision. At the same time, users will develop trust in the GAI systems they frequently use based on their perceived performance. Therefore, generative AI can be regarded as an opinion leader.

Based on the compilation of existing research, the main functions of GAI are as follows: 1. An efficient information summarizer; 2. A creative content producer; 3. A personalized interactive search engine [7]. However, the role of GAI as an opinion leader has not been frequently mentioned. Through comparison, it is found that, unlike traditional social media opinion leaders, it does not merely rely on someone's reputation or the influence of a certain platform, but rather uses its information processing ability, personification interaction, and the perceived authority derived from its output content to influence users' cognition and attitudes, thereby making users want to use it.

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This study will specifically focus on the qualified perspective of GAI as an opinion leader and deeply explore how GAI, as a new type of opinion leader, affects users.

2.2. The role of generative AI in social media

When users start seeking advice from GAI, GAI assumes the role of an opinion leader. GAI needs to possess some characteristics similar to those of an opinion leader in social media. These traits directly affect users' perception of it, their level of trust, and their degree of dependence.

Trust in the GAI platform is a key factor for GAI to exert influence over users. This factor consists of two aspects: trust itself and transparency. The most basic condition for users to accept the information provided by GAI is trust. If users lack trust in the GAI platform, they will not adopt its suggestions at all [8]. Transparency means showing users the working principle and decision-making process of AI, that is, how to provide information to users. This helps alleviate users' concerns about an unknown or even false source of information. When the system is more transparent, users will feel that the information source is more reliable. Therefore, transparency is crucial for building and maintaining trust [9]. In terms of perceived risks, risks such as misinformation, privacy leakage, and algorithm bias can significantly reduce users' willingness to use generative AI [10]. Overall, trust, transparency, and risks together constitute the basic attitude of users towards generative AI, determining whether they are willing to regard it as a trustworthy advisor.

In addition, another important aspect is the content creation ability of generative AI. The first ability is personalization, that is, GAI can provide tailored content based on users' preferences and historical behaviors. This makes the AI's recommendations more precise and attractive. More importantly, GAI can meet users' various needs in specific situations, thereby forming a certain psychological dependence [11]. The second ability is entertainment value. Generative AI can create interesting and fun experiences, helping to establish an emotional connection with users. This pleasant experience will reduce users' criticality, thereby subtly strengthening the degree of GAI's dependence on users [12]. These abilities transform generative AI from a simple tool into an attractive content creator.

The influence of the platform also needs to be taken into account. This is an external factor, similar to the macro environment. When a well-known and reputable platform supports a generative AI product, users' trust in the platform will partially transfer to the AI itself [13]. This "halo effect" leads to two outcomes: it first enhances users' initial trust in the AI's opinions, and at the same time, it creates social influence. Once the platform's influence starts to take shape, users will consider using this AI as a normal thing, or even a new trend, and thus follow suit.

Overall, although previous studies have identified these important features, there is still a lack of a complete framework to demonstrate how these features work together.For now, there isn’t a clear model to explain how they systematically lead users to view generative AI as "opinion leaders". Therefore, this study aims to address this issue. Categorize these features into three clear dimensions: 1) users' attitudes towards generative AI; 2) the content generation capabilities of generative AI; 3) platform influence. Then incorporate these three dimensions into the TAM and UTAUT research models, aiming to clearly describe the internal process by which generative AI, as a new type of opinion leader, influences users' decision-making.

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2.3. The role of generative AI in social media

After a thorough analysis of the mechanism of social media opinion leaders and the functional characteristics of generative AI, this study aims to explore how users accept generative AI as a new type of opinion leader. To achieve this goal, this study uses UTAUT as the main theoretical basis and combines concepts of TAM into it.

In this study, UTAUT was chosen as the main research model because it meets the current research needs and is in line with the TAM model. In the UTAUT model, various driving variables can be fully reflected, such as performance expectancy, effort expectancy, and social influence. At the same time, the core elements of TAM were also incorporated into the model. The concepts proposed by this model, such as perceived usefulness and perceived ease of use, can reflect the decision-making process and influencing factors of GAI users when using the platform.

In the model, This study aims to take the two core concepts of TAM as the theoretical basis for performance expectations and effort expectation in UTAUT. This integration can achieve two goals simultaneously. On the one hand, it can cover the external factors influencing user behavior, and on the other hand, it can deeply analyze users' internal feelings towards the functionality and experience of the technology.

The model framework of this study is suitable for explaining the new technology of generative AI. Generative AI is not only a practical tool but also gives users a sense of social interaction. By adding key feature variables closely related to the role of generative AI as an opinion leader, the model can more accurately reveal which specific attributes of generative AI influence users' adoption decisions, and also explain the psychological mechanism of this process.

3. Research model and hypotheses

This study mainly takes the UTAUT theory as the basic framework. To make the psychological aspect of the model's user behavior more persuasive, this study also specially incorporated the core theory of TAM. In the constructed model, the two concepts of performance expectation and effort expectation in UTAUT actually correspond to perceived usefulness and perceived ease of use in TAM theory. This not only retains the relevant characteristics of TAM theory in understanding user behavior but also enables the analysis to be carried out with the broader and more complete theoretical framework of UTAUT.

Given the particularity of generative AI - which actually plays the role of an opinion leader - this study deliberately incorporates three key sets of influencing factors into the model. These factors include: users' attitudes towards generative AI, such as the degree of trust, perceived risk, and transparency perception; the content generation capabilities of generative AI itself, such as personalization and entertainment value; and platform influence. It is believed that these factors will interact to influence users' perceptions of the technology's performance expectations, effort expectations, and social impact, ultimately driving their willingness to use generative AI. Through such a model design, not only identify which specific characteristics of generative AI have influenced users' adoption decisions, but also step by step demonstrate the changes in users' psychology when generative AI acts as an opinion leader.

3.1. Research hypotheses (H1-H3)

Trust is the most fundamental factor for users to adopt suggestions. When users believe that the assistance provided by generative AI is reliable and beneficial, they are more likely to find it useful,

DOI: 10.54254/2754-1169/2026.NJ30823

thereby enhancing their performance expectations, and easy to use, thereby enhancing their effort expectations [14].

Conversely, in the factor of perceived risk, users have concerns about information errors and privacy issues, which directly undermine their positive evaluations of the performance and ease of use of generative AI [15].

Transparency plays a role by alleviating users' concerns about the unclear source of the content provided by generative AI. This not only enhances users' confidence in the usefulness of AI output, that is, improving performance expectations, but also improves users' perception of system controllability, that is, enhancing effort expectations. Therefore, it is proposed:

H1: Users' attitude toward GAI has a significant positive effect on performance expectations.

H2: Users' attitudes toward GAI significantly and positively influence effort expectations.

Second, it considered that consider GAI's content generation capability. This dimension includes personalization and entertainment value. It focuses on GAI's core value as a "content producer."

Personalization allows GAI to give highly customized content. This significantly improves how relevant the information feels to the user, which increases its perceived usefulness [16].

At the same time, entertainment value creates enjoyable and interesting experiences. This connects with users on an emotional level and indirectly boosts their positive opinion of the AI's functional value—that is, their performance expectations [17].

Together, these two features form GAI's main content-based advantage for getting and keeping users, mainly by affecting how useful they think it is. Therefore, it is propose:

H3: GAI's content generation capability has a significant positive impact on performance expectations.

Finally, platform influence acts as an independent environmental factor. It plays a crucial macro-level role as an endorser.

A powerful and well-known platform can "spill" its own good reputation onto its GAI products. This raises users' first impressions about how well the GAI will perform [18].

Also, a famous platform itself can represent a social norm. Using its GAI products can be seen by users as a social trend or a common thing to do. This feeling strengthens the users' perceived social influence [19]. Therefore, it is proposed:

H4: Platform influence has a significant positive effect on performance expectations.

H5: Platform influence has a significant positive effect on perceived social influence.

3.2. Research hypotheses (H6-H8)

Our research model includes three key mental processes that it is believed are the most direct drivers of user behavior: performance expectancy (how useful the system is), effort expectancy (how easy it is to use), and social influence (what others think). These factors are not new. In fact, many past studies using UTAUT and other earlier models have repeatedly confirmed that these three elements are central to forming a user's intention to use a technology [20].

Based on this strong and consistent evidence from previous literature, it is proposed the following hypotheses for our study:

H6: Performance expectancy has a significant positive effect on usage intention.

H7: Effort expectancy has a significant positive effect on usage intention.

H8: Social influence has a significant positive effect on usage intention.

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3.3. Mediating effect hypotheses (H9-H12)

In our model, its proposed that many external factors do not affect usage intention directly. Through internal psychological processes, it is showed that exactly how these external characteristics eventually influence the user's final decision.

In technology acceptance research, In fact, many previous studies have found that performance expectancy, effort expectancy, and social influence often act as critical mediators in such models [21]. This means they often serve as the psychological bridge between external features and final behavior.

Based on the paths , proposing in our dimensional model (H1 to H5), now formally propose the following mediation hypotheses:

H9: Performance expectancy mediates the relationship between users' attitudes toward GAI and their usage intention.

H10: Effort expectancy mediates the relationship between users' attitudes toward GAI and their usage intentions.

H11: Performance expectancy mediates the relationship between GAI's content generation capabilities and users' usage intentions.

H12: Performance expectancy and social influence jointly mediate the relationship between platform influence and usage intentions.

3.4. Moderating effect hypotheses (H13-H16)

In our model, It is also recognized that not all users are the same. Individual differences between users can change how the model works. These differences set important boundary conditions for the Technology Acceptance Model.

For example, users with high innovativeness are usually more willing to try new technologies. They also tend to be more tolerant of potential problems or flaws. Because of this, it is believed that their positive attitude may not translate as strongly into believing the system is useful. In short, innovative might weaken the influence on attitude and performance expectancy [22].

Age also creates differences. Younger users often care more about what their peers think and are more sensitive to social trends. This likely makes them more affected by social influence when forming their usage intentions.

Studies on gender suggest that female users, when making decisions about technology, might pay more attention to how easy the system is to use [23].

Finally, a user's experience with the system changes their relationship with it. As users gain more experience, they become familiar with the system. At this point, the importance of basic usability (ease of use) in their decision-making process generally goes down [24]. Thus, some hypotheses can be made:

H13: User innovative negatively moderates the attitude-performance expectancy relationship.

H14: User age negatively moderates the social influence-usage intention relationship.

H15: User gender positively moderates the effort expectancy-usage intention relationship.

H16:User experience negatively moderates the effort expectancy-usage intention relationship.

3.5. Research model

This study constructed the following model. This model integrates six key factors, such as trust, transparency, personalization, platform influence, entertainment value, and perceived risk, into the

DOI: 10.54254/2754-1169/2026.NJ30823

theoretical framework of UTAUT.

In this model architecture, performance expectancy, effort expectancy, and social influence constitute the core mediating mechanisms. This model also incorporates four moderating variables: user innovativeness, age, gender, and usage experience, to reveal the mechanism by which generative AI, as an opinion leader, influences users' intention to use.This provides theoretical support for understanding novel influence patterns in human-computer interaction. The research model is illustrated in Figure 1.

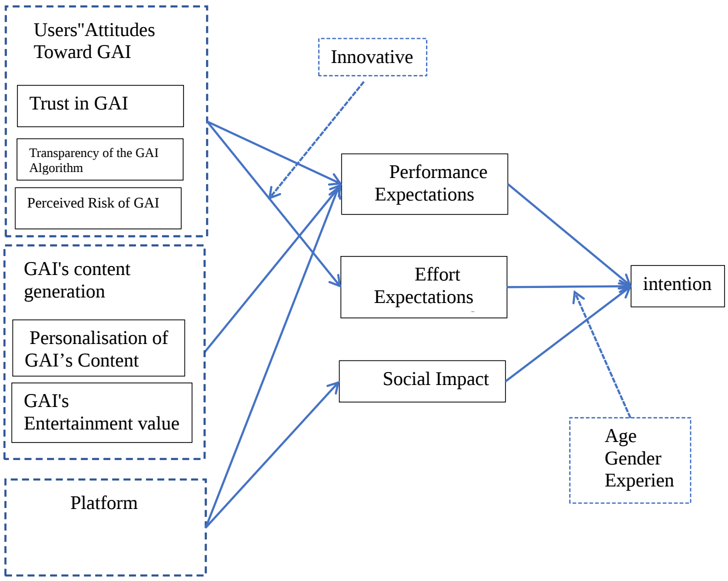

Figure 1. Study model

4. Data collection and processing

This study collected data through an online questionnaire distributed via social platforms such as WeChat. A total of 851 responses were received. After excluding respondents who had never used generative AI, 823 valid questionnaires were retained, resulting in a valid response rate of 96.71%.

The valid data were analyzed using SPSS 25.0. Basic demographic information of the sample is presented in Table 1.

As shown in Table 1, the gender distribution of the data sample is basically balanced, with 49.09% being male and 50.91% being female. In terms of age distribution, the group aged 36-45 has the highest proportion, reaching 21.63%. Regarding usage experience, the group that occasionally uses generative AI a few times a month is the largest, accounting for 21.99% of the total sample. Therefore, in the subsequent analysis of the moderating effect of experience in this study, this group will be mainly used as the research basis.

Based on the results of reliability and validity analysis, the data of this study have good reliability and validity. In terms of reliability, the Cronbach's α coefficient of all dimensions is higher than 0.7, and the CITC value of each item is greater than 0.4, indicating that the internal consistency of the scale is high and the reliability quality is good, and no items need to be deleted. In terms of validity, the KMO value is 0.942, and the Bartlett's sphericity test is significant ($p < 0.05$), indicating that the data are very suitable for factor analysis; exploratory factor analysis extracted a total of 12 common factors, with a cumulative variance explanation rate of 76.692%, and after rotation, the loadings of each item on their corresponding factors are all greater than 0.5, and the structural validity is ideal.

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In conclusion, the reliability and validity of the questionnaire data meet the research standards and can be used for subsequent analysis.

Table 1. Frequency analysis results

Variable	Option	Frequency	Percentage (%)	Cumulative Percentage (%)
Gender	Male	404	49.09	49.09
	Female	419	50.91	100
Age	≤18	157	19.08	19.08
	19–25 years	149	18.1	37.18
	26–35 years old	169	20.53	57.72
	36–45 years old	178	21.63	79.34
	≥46	170	20.66	100
Experience	Never used	147	17.86	17.86
	Heard of but never used	163	19.81	37.67
	Occasional use (a few times a month)	181	21.99	59.66
	Frequent use (several times a week)	158	19.2	78.86
	Almost daily use	174	21.14	100

4.1. Reliability and validity analysis

It is used to regression analysis to test the relationships in our research model. The main results are shown in Table 2.

Users' attitudes towards generative AI significantly influence their usage expectations. Data shows that trust has a positive impact on performance expectations (β=0.185, $p<0.001$) and effort expectations (β=0.290, $p<0.001$). Transparency also has a significant positive effect on performance expectations (β=0.106, $p<0.05$) and effort expectations (β=0.292, $p<0.001$). However, perceived risk shows a significant negative impact on both performance expectations (β=-0.168, $p<0.001$) and effort expectations (β=-0.223, $p<0.001$).

In addition, the content generation capability of generative AI has significantly raised users' performance expectations. Personalization (β=0.146, $p<0.001$) and entertainment value (β=0.147, $p<0.01$) both demonstrated positive effects.

Moreover, the influence of the platform also plays a crucial role. It not only directly boosts performance expectations (β=0.212, $p<0.001$), but also significantly enhances social influence (β=0.660, $p<0.001$).

Finally, the core constructs of UTAUT exhibit strong predictive power for the intention to use. Performance expectations (β=0.364, $p<0.001$), effort expectations (β=0.214, $p<0.001$), and social influence (β=0.191, $p<0.001$) all show significant positive impacts.

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Table 2. Simulated path regression results

Path			Estimate	S.E.	C.R.	P	Standard Estimate
Performance Expectations	<---	Trust in GAI	0.213	0.054	3.961	***	0.185
Effort Expectation	<---	Trust in GAI	0.311	0.048	6.527	***	0.29
Performance Expectations	<---	Transparency of GAI Algorithm	0.102	0.042	2.421	0.015	0.106
Effort Expectation	<---	Transparency of the GAI Algorithm	0.262	0.041	6.437	***	0.292
Performance Expectations	<---	Personalisation of Generative AI Content	0.161	0.045	3.588	***	0.146
Performance Expectations	<---	Platform Influence	0.203	0.051	3.981	***	0.212
Social Impact	<---	Platform Influence	0.62	0.038	16.373	***	0.66
Performance Expectations	<---	GAI's Entertainment Value	0.154	0.049	3.117	0.002	0.147
Performance Expectations	<---	Perceived Risk of GAI	-0.163	0.043	-3.775	***	-0.168
Effort Expectation	<---	GAI's Perceived Risk	-0.201	0.038	-5.28	***	-0.223
Usage Intention	<---	Performance Expectations	0.366	0.044	8.319	***	0.364
Usage Intention	<---	Effort Expectations	0.232	0.04	5.737	***	0.214
Usage Intention	<---	Social Impact	0.195	0.038	5.121	***	0.191

4.2. Mediating effect test

Table 3. Mediation effect test

Path	Estimate	Lower	Upper	P
Trust in GAI → Performance Expectations → Usage Intent	0.078	0.035	0.142	0.000
Transparency of GAI algorithm → Performance expectations → Usage intention	0.037	0.007	0.078	0.012
Generative AI Content Personalisation → Performance Expectations → Usage Intent	0.059	0.026	0.101	0.001
Platform influence → Performance expectations → Usage intent	0.074	0.032	0.131	0.000
GAI's entertainment value → Performance expectations → Usage intention	0.056	0.018	0.106	0.003
Perceived risk of GAI → Performance expectations → Usage intention	-0.06	-0.111	-0.025	0.000
Trust in GAI → Effort Expectations → Usage Intentions	0.072	0.037	0.126	0.000
Transparency of GAI algorithm → Effort expectation → Usage intention	0.061	0.033	0.099	0.000
Perceived Risk of GAI → Effort Expectation → Usage Intention	-0.047	-0.085	-0.022	0.000
Platform Influence → Social Influence → Usage Intention	0.121	0.062	0.188	0.000

The results shown in Table 3 illustrate the influence of the mediating paths. Specifically, trust affects the intention to use by enhancing users' perception of the usefulness of AI (effect value = 0.078, 95% confidence interval [0.035, 0.142]) and the perception of ease of use (effect value = 0.072, 95% confidence interval [0.037, 0.126]). Similarly, transparency also exerts its influence by enhancing the perception of usefulness (effect value = 0.037, 95% confidence interval [0.007, 0.078]) and the perception of ease of use (effect value = 0.061, 95% confidence interval [0.033, 0.099]). On the other hand, perceived risk weakens the intention to use by reducing users' evaluation of the usefulness of AI (effect value = -0.06, 95% confidence interval [-0.111, -0.025]) and increasing the perception of difficulty in use (effect value = -0.047, 95% confidence interval [-0.085, -0.022]).

Regarding the content generation capabilities of generative AI, both personalization (effect value = 0.059, 95% confidence interval [0.026, 0.101]) and entertainment value (effect value = 0.056, 95%

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confidence interval [0.018, 0.106]) significantly influence the intention to use by enhancing users' perception of the usefulness of AI.

Platform influence works through two different paths. Firstly, by enhancing performance expectations (effect value = 0.074, 95% confidence interval [0.032, 0.131]), and secondly, by strengthening social influence (effect value = 0.121, 95% confidence interval [0.062, 0.188]) to affect the intention to use.

4.3. Analysis of moderating variables

Moderating effect of innovative on the relationship between trust in GAI and performance expectations.

Table 4. Moderation analysis results about trust (performance expectations)

	B	se	t	p
constant	3.440***	0.028	121.113	0.000
Trust in GAI	0.336***	0.034	10.007	0.000
Innovativeness	0.178***	0.035	5.137	0.000
Trust in GAI*Innovation	-0.190***	0.029	-6.551	0.000
R	0.528			
R^2	0.279			
F	F (3,819) = 105.476, p = 0.000			

* p < 0.05 ** p < 0.01 *** p < 0.001

As the table 4 shows, the independent variable, namely trust in GAI, and the moderating variable, namely innovativeness, were centered. An interaction term was created by multiplying these two variables. The analysis results showed that the interaction effect was significant (β = -0.190, p < 0.05). This finding indicates that innovativeness does indeed moderate the relationship between trust and performance expectations, which can be seen in Figure 2.

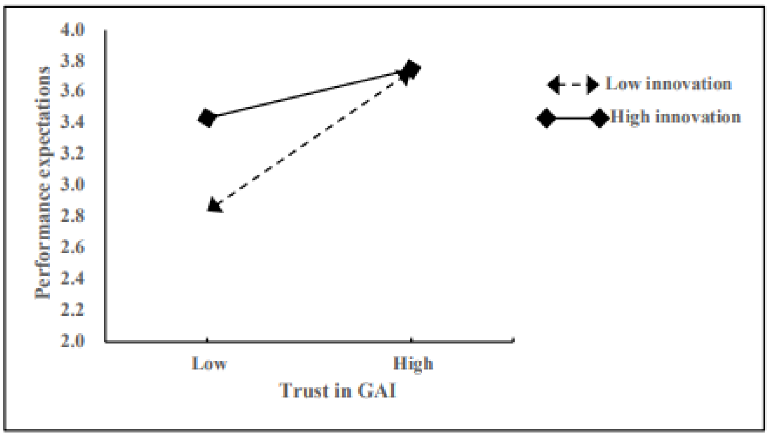

Figure 2. The moderating effect about trust in GAI

Innovation moderates the relationship between perceived risk of GAI and performance expectations.

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Table 5. Moderation analysis results about risk (performance expectations)

	B	se	t	p
constant	3.444***	0.028	124.147	0.000
GAI's Perceived Risk	-0.330***	0.03	-11.062	0.000
Innovation	0.209***	0.033	6.284	0.000
Perceived Risk of GAI*Innovativeness	0.224***	0.028	7.967	0.000
R	0.546			
R^2	0.298			
F	F (3,819) = 116.011, p = 0.000			

* p < 0.05 ** p < 0.01 *** p < 0.001

It could be found in Table 5, The independent variable and moderator variable were first centered in the analysis. Their product term was then calculated and treated as the interaction term. Through regression analysis, the moderating effect was carefully examined. When the product of GAI's perceived risk and innovation was introduced into the regression equation, the interaction coefficient was found to be 0.224. It can be seen that the p-value for this coefficient was less than 0.05. This result means that the relationship between GAI's perceived risk and performance expectations is actually moderated by innovation,as the Figure 3 shows.

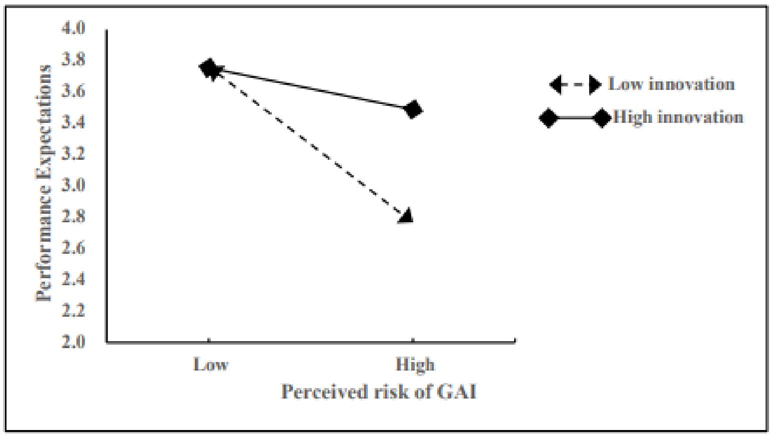

Figure 3. The moderating effect about perceived risk of GAI

As the table 6 shows, the independent variable and moderator variable were centered, and their product was used as interaction term. Through regression analysis, the moderating effect was tested. When the product of social influence and age was put into regression equation, the result got an interaction coefficient of -0.095, with p-value less than 0.05. It can be seen that this means age moderates the relationship between social influence and usage intention.The result shows in Figure 4.

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Table 6. Moderation analysis results about social influence (usage intention)

	B	se	t	p
constant	3.778***	0.025	148.617	0.000
Social influence	0.353***	0.029	12.278	0.000
Age	0.283***	0.018	15.641	0.000
Social Influence*Age	-0.095***	0.02	-4.841	0.000
R	0.641			
R^2	0.411			
F	F (3,819) = 190.456, p = 0.000			

* p < 0.05 ** p < 0.01 *** p < 0.001

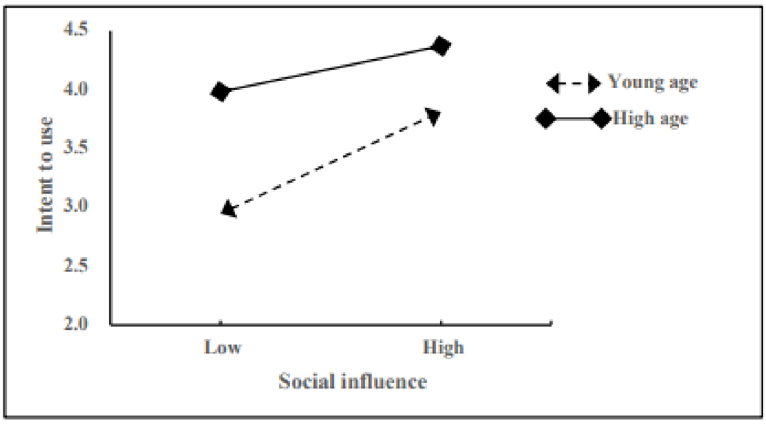

Figure 4. The moderating effect about social influence

Table 7. Moderation analysis results about effort expectations (usage intention)

	B	se	t	p
constant	3.751***	0.028	136.36	0.000
Effort Expectation	0.502***	0.031	16.217	0.000
Gender	-0.059	0.055	-1.074	0.283
Effort Expectations*Gender	0.345***	0.062	5.567	0.000
R	0.514			
R^2	0.264			
F	F (3,819)=98.136, p=0.000			

* p < 0.05 ** p < 0.01 *** p < 0.001

As the table 7 shows, the independent variable and moderator variable were centered, and their product was made as interaction term. Through regression analysis, the moderating effect was checked. When the product of effort expectation and gender was put into regression equation, the result got an interaction coefficient of -0.095, with p-value less than 0.05. It can be shown in Figure 5.

DOI: 10.54254/2754-1169/2026.NJ30823

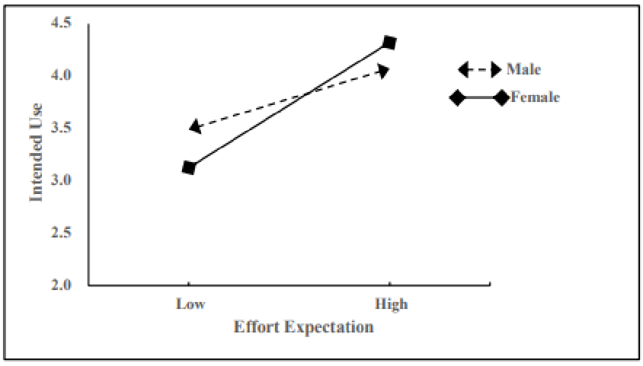

Figure 5. The moderating effect about effort expectation on gender

Table 8. Moderation analysis results about effort expectations (usage intention)

	B	se	t	p
constant	3.763***	0.026	147.458	0.000
Effort Expectation	0.401***	0.029	13.896	0.000
Experience	0.266***	0.018	14.542	0.000
Effort Expectations*Experience Experience	-0.058**	0.02	-2.881	0.004
R	0.63			
R^2	0.398			
F	F (3,819)=180.118, p=0.000			

* p < 0.05 ** p < 0.01 *** p < 0.001

It could be found in table 8, the independent variable and moderator variable were centered, and their product was made as interaction term. Through regression analysis, the moderating effect was checked. When the product of effort expectation and experience was put into regression equation, the result got an interaction coefficient of -0.058, with p-value below 0.05. It can be seen this means experience moderates the relationship between effort expectation and usage intention, showing in Figure 6.

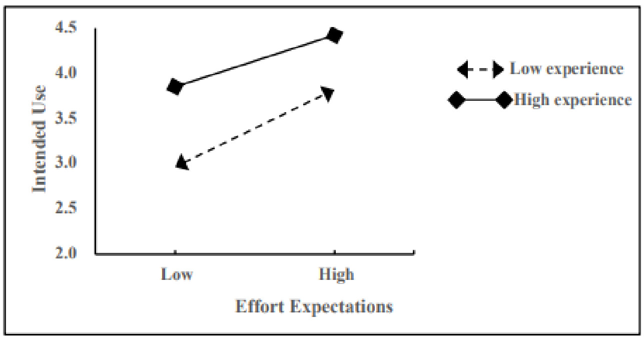

Figure 6. The moderating effect about effort expectation on experience

Overall, regarding the aspect of whether users are innovative, the data from this study shows that it has a significant negative moderating effect on the relationship between user attitudes and performance expectations (β = -0.190, p < 0.001), which indicates that H13 holds true. Meanwhile,

DOI: 10.54254/2754-1169/2026.NJ30823

it exhibits a significant positive moderating effect on the relationship between perceived risk and performance expectations ($\beta = 0.224$, $p < 0.001$), suggesting that H14 is also valid.

Age had a significant negative moderating effect on the relationship between social influence and usage intention ($\beta = -0.095$, $p < 0.001$), thus H15 was supported. Gender, on the other hand, had a significant positive moderating effect on the relationship between effort expectancy and usage intention ($\beta = 0.345$, $p < 0.001$), and H16 was supported. Finally, usage experience showed a significant negative moderating effect on the relationship between effort expectancy and usage intention ($\beta = -0.058$, $p < 0.01$), and therefore H18 was supported.

5. Conclusion

Users' trust in generative AI, algorithm transparency, content personalization, platform influence, and entertainment value can all effectively enhance perceived usefulness and perceived ease of use. However, perceived risk has a significant negative impact on both dimensions. These factors mainly influence the intention to use through indirect pathways. They exert their effects by influencing the three mediating variables of perceived usefulness, perceived ease of use, and social influence.

This study also verified several key moderating effects. Users with high innovativeness have a lower reliance on trust and are less sensitive to risks; younger users are more susceptible to the influence of social impact; female users place greater emphasis on system ease of use. Moreover, as users accumulate experience, their focus on ease of use gradually weakens.

Based on these conclusions, it is suggested that relevant platforms and policymakers can take actions from three levels: technology, strategy, and user operation. Technologically, they should explain the algorithm design and operation mechanism of the application to users as much as possible. Strategically, they can enhance their platform influence by cooperating with well-known brands. In terms of user operation, they should implement differentiated strategies for different user groups, such as optimizing ease of use for female users, providing guidance tutorials for novices, and opening advanced functions for experienced users. Female users think ease of use is more important. Experienced users don't focus too much on ease of use anymore.

All these findings help us understand how generative AI becomes accepted by users as a "mimetic opinion leader".

To help more users accept generative AI, it is suggested some strategies:

For technology aspects, platforms should build fact-checking systems and explain how AI works to make it more credible and transparent. They should also develop personalised services across different sessions and use emotional design to improve user experience.

For strategy aspects, trust can be improved by working with well-known brands. Platforms should also communicate about risks actively to manage user expectations.

For user operations, platforms should use different strategies for different user groups. They should design functions, marketing messages and interface interactions according to users' innovation levels, ages and genders. For example, make the system easier to use for female users, provide guidance for new users, and open advanced features for experienced users. These methods can help achieve better optimisation and keep users engaged.

References

[1] Ballesteros, M. A., Acosta-Enriquez, B. G., Valle, M. d. l. A. G., Morales-Angaspilco, J. E., Callejas Torres, J. C., Luján López, J. E., Blanco-García, L. E., García Juárez, H. D., & Jordan, O. H. (2025). The influence of social norms and word-of-mouth marketing on behavioural intention and behavioural use of generative AI chatbots among

DOI: 10.54254/2754-1169/2026.NJ30823

university students. Computers in Human Behavior Reports, 19, 100760. https: //doi.org/10.1016/j.chbr.2025.100760
[2] Li, S., Fan, S., & Demartini, G. (2025). The interaction between emotion dynamics and opinion changes in the era of generative AI. Computers in Human Behavior Reports, 19.
[3] Basha, M., & Gema Rodríguez-Pérez. (2025). Trust, transparency, and adoption in generative AI for software engineering: insights from Twitter discourse. Information and Software Technology.
[4] Das, S., & Kaur, M. (2025). Social Media Analysis in Public Opinion: A Review. International Conference on Smart Cyber Physical Systems. Springer, Singapore.
[5] Larisu, Z., & Zulham, Z. (2024). Crisis communication on social media: managing reputation and maintaining public trust. Journal of Dialogos, 1(4), 19–29.
[6] Suk, J., Zhang, Y., Liu, J., & Yang, Y. (2025). Communicative AI in the scientific public sphere: an analysis of Twitter discourse on generative AI tools. Telematics and Informatics, 98.
[7] Huang, J., & Zhou, A. (2025). Generative AI outperforms humans in social media engagement: Evidence from GPT-4 and the FIIT model. Public Relations Review, 51(5), 102643. https: //doi.org/10.1016/j.pubrev.2025.102643
[8] Piller, F. T., Srour, M., & Marion, T. J. (2024). Generative AI, innovation, and trust. The Journal of Applied Behavioural Science, 60(4), 613–622.
[9] Diega, G. N. L., & Bezerra, L. C. T. (2024). Can there be responsible AI without AI liability? Incentivising generative AI safety through ex-post tort liability under the EU AI Liability Directive. International Journal of Law and Information Technology, 32(000).
[10] Kim, D., Kim, S., Kim, S., & Lee, B. H. (2024). Generative AI characteristics, user motivations, and usage intention. Journal of Computer Information Systems, 1–16.
[11] Yuan X, Ding Z, Zhang Z, et al. (2025). Personalised learning resources created by generative artificial intelligence: A systematic review [C]//2025 11th International Conference on Education and Training Technologies (ICETT). IEEE, 2025: 84-89.
[12] Duron, L., Soyer, P., & Lecler, A. (2025). Generative AI smartphones: from entertainment to potentially serious risks in radiology. Diagnostic and Interventional Imaging, 106(2).
[13] Lee S, Suh S J, Chun J S. (2025). A Society that Encourages AI: The Impact of Social Influence Factors on the Adoption of Generative AI Based on Cognitive Appraisal Theory [J]. Asian Communication Research, 22(1), 49-70.
[14] Shao, C. , Nah, S. , Makady, H. , & Mcnealy, J. . (2025). Understanding user attitudes towards ai-enabled technologies: an integrated model of self-efficacy, tam, and ai ethics. International journal of human-computer interaction(5), 41.
[15] Saputra, S. , Selli, S. , & Yuwono, W. . (2025). The influence of customer experience, perceived ease of use, perceived usefulness, perceived risk on behavioral intention to use mobile banking in malaysia. EKOMBIS REVIEW: Jurnal Ilmiah Ekonomi dan Bisnis, 13(1).
[16] Qiao, C. (2025). The impact of social media on brand perception and consumer behaviour. Highlights in Business Economics and Management, 52, 27-33.
[17] Zeng, J., Yang, J., Malik, W., Yan, X., Huang, R., & He, Q. (2023). Let AI entertain you: increasing user engagement with generative AI and rejection sampling.
[18] Scofield, C. L. (2025). Assessing author authority and blog influence - Amazon Technologies, Inc.
[19] El-Merabet, O. , Kinani, S. , & El-Merabet, Z. . (2025). How social media-based brand communities influence the choice intention of higher education institutions: the mediating role of brand attitude. International Review on Public and Nonprofit Marketing(2), 1-24.
[20] Xia, Y., & Chen, Y. (2025). Driving factors of generative AI adoption in new product development teams from a UTAUT perspective. International Journal of Human-Computer Interaction, 10, 41.
[21] Jeong, S., Kim, S., & Lee, S. (2025). Effects of Perceived Ease of Use and Perceived Usefulness of Technology Acceptance Model on Intention to Continue Using Generative AI: Focusing on the Mediating Effect of Satisfaction and Moderating Effect of Innovation Resistance. International Conference on Conceptual Modelling. Springer, Cham.
[22] Marak, Z. R., Pahari, S., Shekhar, R., Tiwari, A., & Carayannis, E. G. (2025). Factors affecting chatbots in banking services: the UTAUT2 and innovation resistance theory perspective. Journal of Innovation & Entrepreneurship, 14(1).
[23] Lee, K., & Park, J. P. (2023). A study on the intention to use internet-only banks integrating UTAUT-2 and TRI: the moderating effects of gender and age. Journal of the Korea Contents Association.
[24] Admassu, W., & Gorems, K. (2024). Analysing health service employees' intention to use e-health systems in southwest Ethiopia: using the UTAUT-2 model. BMC Health Services Research, 24(1).