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Analysis of Key Factors in Corporate Adoption of Generative Artificial Intelligence Based on the UTAUT2 Model

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[Abstract]

Generative Artificial Intelligence (AI) has become the focus of societal attention due to its wide range of applications and profound impact. This paper constructs a comprehensive theoretical model based on the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), integrating variables such as Personal Innovativeness and Perceived Risk to study the key factors influencing enterprises' adoption of Generative AI. We employed Structural Equation Modeling (SEM) to verify the hypothesized paths and used the Bootstrapping method to test the mediating effect of Behavioral Intention. Additionally, we explored the moderating effect of Perceived Risk through Hierarchical Regression Analysis. The results indicate that Performance Expectancy, Effort Expectancy, Social Influence, Price Value, and Personal Innovativeness have significant positive impacts on Behavioral Intention. Behavioral Intention plays a significant mediating role between these factors and Use Behavior, while Perceived Risk negatively moderates the relationship between Behavioral Intention and Use Behavior. This study provides theoretical and empirical support for how enterprises can effectively adopt Generative AI, offering important practical implications.

▸ **Key words**: Generative AI, Acceptance, UTAUT2, Personal Innovativeness, Perceived Risk

[요 약]

생성형 인공지능은 그 광범위한 응용 범위와 깊은 영향력으로 인해 사회의 주목을 받고 있습니다. 본 논문은 통합 기술 수용 및 사용 이론 2(UTAUT2)를 기반으로 개인의 혁신성과 인지된 위험 등의 변수를 결합하여, 기업이 생성형 인공지능을 채택하는 데 영향을 미치는 주요 요인을 연구하기 위해 종합적인 이론 모델을 구축하였습니다. 우리는 가설 경로를 검증하기 위해 구조 방정식 모델(SEM)을 사용하였고, 부트스트래핑 방법을 통해 수용 의향의 매개 효과를 검증하였으며, 계층적 회귀 분석을 통해 인지된 위험의 조절 효과를 탐구하였습니다. 연구 결과, 성과 기대, 노력 기대, 사회적 영향, 가치 평가 및 개인 혁신성이 수용 의향에 긍정적인 영향을 미치며, 수용 의향은 이러한 요인들과 사용 행동 사이에서 중요한 매개 역할을 한다는 것이 밝혀졌습니다. 반면, 인지된 위험은 수용 의향과 사용 행동 사이에서 부정적인 조절 효과를 가지는 것으로 나타났습니다. 본 연구는 기업이 생성형 인공지능을 효과적으로 채택하는 방법에 대해 이론적 근거와 실증적 지원을 제공하며, 중요한 실무적 의의를 가집니다.

▸ **주제어**: 생성적 인공지능, 수용도, UTAUT2, 개인 혁신성, 인식된 위험

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I. Introduction

Since the advent of ChatGPT, generative artificial intelligence (Gen AI) has garnered widespread attention not only in the technological domain but also in business and daily life, showcasing its unique value and rapidly becoming a focal point of research and application. This technology, with its exceptional natural language processing capabilities and its ability to understand and generate complex textual content, is profoundly transforming our work and daily lives. According to Similarweb's survey data, ChatGPT reached 100 million monthly active users just two months after its launch, making it the fastest-growing consumer application in history. McKinsey's report, "The Economic Potential of Generative AI: The Next Productivity Frontier," predicts that generative AI will contribute $2.6 to $4.4 trillion to the global economy annually. At the 2024 Davos World Economic Forum, Deloitte's report, "The State of Enterprise Generative AI Applications: Standing Firm and Planning Ahead," revealed that 79% of surveyed corporate executives expect generative AI to drive enterprise transformation within the next three years.

Generative Artificial Intelligence (Gen AI) is an AI algorithm focused on generative modeling, with its core objective being to learn the probability distribution of training samples and generate new samples accordingly [1]. This AI technology demonstrates significant capabilities in understanding and generating natural language, efficiently creating realistic data, enhancing machine learning datasets, and generating personalized content. Based on its functionalities, generative AI technology can be categorized into text generation, image creation, and data simulation. In terms of text generation, generative AI can automatically produce high-quality text. For instance, ChatGPT is widely used in the field of natural language processing for content creation and news writing. In the area of image creation [2], generative AI technology can be used to generate realistic images and artworks. For example, NVIDIA's Generative Adversarial Networks (GANs) are used to create high-quality virtual images, which are widely applied in game development and movie special effects. In terms of data simulation, generative AI can generate simulated data for training machine learning models and performing predictive simulations. Additionally, generative AI has spurred innovations in various fields, including language processing [3], architectural design [4], industrial IoT [5], education [6], and journalism [7], showcasing its broad application prospects and innovation-driving capabilities.

Currently, research on generative AI primarily focuses on areas such as image and visual computing, natural language processing, data augmentation and simulation, and creative content generation. However, there is still a relative lack of in-depth research on how enterprises accept and use this technology. In particular, there is a need for deeper exploration of the application challenges enterprises face, the adaptability of organizational culture, and the difficulties of technological integration and implementation when introducing generative AI technology. Therefore, this paper attempts to construct a model based on the UTAUT2 framework, integrating key variables such as Personal Innovativeness and Perceived Risk, to investigate the factors influencing the acceptance of generative AI. The aim is to reveal how these factors impact the acceptance of generative AI, thereby providing strategic guidance for enterprise decision-makers and technology developers to effectively promote and apply generative AI technology in enterprise environments.

II. Theoretical Background

1. UTAUT2 Model

In the field of technology application research, it is crucial to deeply analyze the factors that influence user acceptance and use of new technologies. Historically, numerous theoretical frameworks have emerged, such as the Technology Acceptance Model (TAM) and the Theory of Reasoned Action (TRA). To enhance the explanatory power of these models, Venkatesh and colleagues integrated eight theoretical models, including TAM, TRA, the Motivational Model (MM), and Social Cognitive Theory (SCT), to form the Unified Theory of Acceptance and Use of Technology (UTAUT) [8]. This theory synthesizes four core constructs—Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions—along with four moderating variables: gender, age, experience, and voluntariness. In 2012, Venkatesh et al. further extended the UTAUT model by adding three new constructs—Hedonic Motivation, Price Value, and Habit—and removing the voluntariness moderator, thus proposing the UTAUT2 model [9]. UTAUT2 not only enhances the generalizability of the model but also introduces new variables to capture more dimensions of consumer behavior, making the theory more refined and practical. UTAUT2 has become one of the most effective theoretical models for explaining technology acceptance and usage behavior, with an explanatory power of 74%, surpassing the original UTAUT theory [10]. It has been widely applied and validated across various fields [11-13]. Given that Generative Artificial Intelligence (Gen AI) is an emerging information technology, the UTAUT2 model is highly suitable for studying the factors influencing its acceptance.

2. Personal Innovativeness

Individuals' attitudes towards innovation and their learning ability play a crucial role in technology acceptance and usage behavior. The Diffusion of Innovations Theory defines this trait as Personal Innovativeness, which refers to an individual's tendency to adopt new ideas earlier than other members of a group [14]. Research in areas such as AI voice assistants [15], AI applications within organizations [16], and robotics technology [17] has shown that Personal Innovativeness significantly affects technology acceptance. Users with high Personal Innovativeness are more likely to actively accept and explore Generative AI, becoming early adopters and active users. Considering that the UTAUT2 model originally did not include the dimension of Personal Innovativeness, incorporating this variable into the model helps to gain a deeper understanding of technology acceptance and usage behavior.

3. Perceived Risk

The Perceived Risk Theory posits that individuals consider potential negative consequences when making choices, and this risk assessment influences their attitudes and adoption decisions regarding specific technologies. When faced with emerging Generative AI technology, users may have concerns about its safety, privacy protection, and accuracy. These perceived risk factors can significantly impact user acceptance and behavior. Studies in various fields, including digital personal data storage [18], blockchain technology adoption [19], and remote medical consultation services [20], have confirmed the significant impact of perceived risk on technology acceptance. Therefore, incorporating perceived risk into the UTAUT2 model provides a more comprehensive and in-depth framework for understanding and predicting users' acceptance and use of Generative AI.

III. Research Model and Hypothese

1. Research Model

Generative Artificial Intelligence (Gen AI) is a rapidly evolving frontier technology that is profoundly influencing enterprise operations and decision-making. The characteristics that enterprises exhibit when adopting this technology differ significantly from the traditional UTAUT2 model. Therefore, this study constructs a multidimensional research model based on the Unified Theory of Acceptance and Use of Technology (UTAUT2) framework, incorporating core concepts from the Diffusion of Innovations Theory and Perceived Risk Theory.

Generative AI technology garners significant attention due to its wide application prospects and substantial economic potential. When enterprises observe their competitors successfully implementing generative AI and achieving notable results, they are strongly motivated to follow suit. Additionally, discussions on social media and positive feedback from early adopters spread rapidly, creating a powerful network effect. These external factors influence enterprise choices, making it reasonable and necessary to include "Social Influence" in the research model.

The ability of generative AI to adapt to enterprises is a crucial factor affecting its acceptance. Enterprises expect generative AI to optimize decision-making processes, enhance operational efficiency, improve execution outcomes, and provide innovative solutions. This high level of expectation for the technology boosts enterprises' willingness to accept generative AI. Therefore, incorporating Performance Expectancy into the analytical framework is vital.

The effort required for users to learn and adapt to generative AI technology, including handling complex algorithms, processing intricate data, and understanding new interfaces, directly impacts their willingness to accept it. If users perceive the learning and usage process as overly cumbersome or difficult, their willingness to accept the technology may significantly decrease. Thus, incorporating Effort Expectancy into the analytical framework helps more accurately evaluate users' acceptance of generative AI.

Introducing generative AI requires breaking existing work patterns, continuously adjusting and optimizing workflows, and flexibly applying the technology in diverse scenarios, necessitating employees to constantly learn and adapt to new technologies. Furthermore, the application of generative AI entails certain risks, and employees must be capable of handling the uncertainties brought by innovation. Therefore, assessing employees' willingness and ability to explore and adapt to new technologies, termed as Personal Innovativeness, becomes a critical factor influencing the acceptance of generative AI. Including Personal Innovativeness in the analytical framework is essential for a comprehensive evaluation of this impact.

Perceived Risk is closely related to individuals' willingness to accept new technology, especially regarding the safety of generative AI, such as concerns about data breaches, privacy violations, and the reliability of generated content. Practical experience shows that even with a high willingness to accept, strong risk perception can inhibit usage behavior. This indicates that Perceived Risk might moderate the relationship between Acceptance Intention and Use Behavior, potentially altering or adjusting the strength of this relationship. Thus, including Perceived Risk as a moderating variable in the research model enables a more accurate mapping of user behavior when facing generative AI.

In today's increasingly digital environment, the platforms for generative AI, such as computers, smartphones, and networks, are widely used, allowing employees to utilize them seamlessly in various environments. Hence, the "Facilitating Conditions" variable is excluded when constructing the model. Considering generative AI as an emerging technology, users' habits regarding this technology are still forming and evolving, and relevant "Habit" data may lack reliability. Including the Habit variable during the initial technology adoption phase might not accurately reflect user acceptance and could potentially affect the model's accuracy, leading to its exclusion. Additionally, enterprises' decisions to adopt generative AI technology are typically based on rational considerations of cost-effectiveness, performance improvement, and strategic advantages, focusing on practicality and professionalism rather than Hedonic Motivation. Therefore, the Hedonic Motivation variable is also excluded from the research framework.

In summary, this paper focuses on six core variables from the UTAUT2 model: Performance Expectancy, Effort Expectancy, Social Influence, Price Value, Acceptance Intention, and Use Behavior. By integrating Personal Innovativeness and Perceived Risk, a comprehensive research model is constructed (see Figure 1) to explore the multifaceted factors influencing enterprises' acceptance of generative AI.

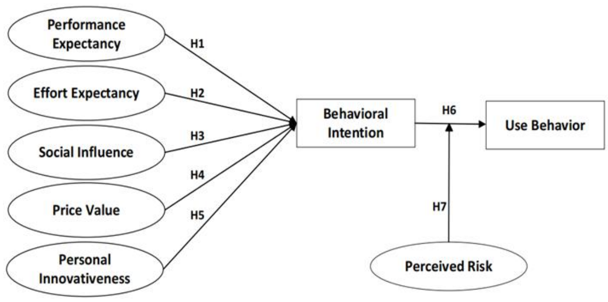

Fig. 1. System Architecture

2. Research Hypotheses

2.1 ModelDirect Impact Path Hypotheses

(1) Performance Expectancy refers to an individual's belief that using a technology will help improve their job performance [8]. In the UTAUT2 model, Performance Expectancy has been shown to have a significant positive impact on technology acceptance intention. Additionally, numerous empirical studies [21][22][23] support the positive effect of Performance Expectancy on technology acceptance intention. In this paper, Performance Expectancy reflects users' expectations that generative AI will enhance work efficiency, task accuracy, and innovation. Given generative AI's notable advantages in deep learning, natural language processing, and predictive analysis, the following hypothesis is proposed:

H1: Performance Expectancy positively influences users' acceptance intention of generative AI.

(2) Effort Expectancy is defined as an individual's perceived ease of use when adopting new technology, focusing on the difficulty level of technology adoption and mastery. Effort Expectancy has been shown in existing studies to have a significant positive impact on technology acceptance intention [24][25][26]. In the context of generative AI application, Effort Expectancy primarily involves the user-friendliness of the technology, intuitive interfaces, understandable functional designs, and a low learning curve. These features are significant advantages of generative AI, collectively reducing users' perceived difficulty and thereby significantly enhancing their acceptance intention. Therefore, the following hypothesis is proposed:

H2: Effort Expectancy positively influences users' acceptance intention of generative AI.

(3) Social Influence refers to the impact of an individual's social environment on their decision-making, including factors such as colleagues, industry leaders, and opinion leaders on social media. Numerous academic literature has indicated that Social Influence has a significant positive effect on technology acceptance intention [27][28]. In the rapidly developing context of generative AI technology, its widespread application in daily life and professional fields not only creates significant social impacts but also influences enterprises and individuals' adoption decisions. In this context, Social Influence is reflected in the recognition of the technology by professional communities, industry trends, media coverage, and the adoption stance of market leaders and competitors, all of which collectively affect enterprises' acceptance and adoption decisions of generative AI. Therefore, the following hypothesis is proposed:

H3: Social Influence positively influences users' acceptance intention of generative AI.

(4) Price Value refers to users' evaluation of the potential benefits versus the costs when considering adopting new technology. This evaluation involves comparing the benefits brought

by the technology (such as convenience, efficiency improvement, functionality) with its potential costs (such as monetary costs, learning costs, usage risks). Price Value has also been shown to positively influence acceptance intention [29][30][31]. In this paper, Price Value is defined as the comprehensive evaluation by enterprise users of the potential benefits and costs when considering the adoption of generative AI. If enterprise users believe that the benefits of generative AI, such as efficiency improvement, innovation enhancement, and decision support, outweigh its implementation costs, such as investment, training, and maintenance expenses, it indicates a positive Price Value. Based on this, enterprise users show stronger acceptance intention towards the adoption and application of generative AI. Therefore, the following hypothesis is proposed:

H4: Price Value positively influences users' acceptance intention of generative AI.

(5) Personal Innovativeness, as a key indicator of an individual's acceptance of new technology or concepts, reflects an individual's curiosity, openness, and adaptability to new things [32]. Existing studies have confirmed that Personal Innovativeness has a significant positive impact on acceptance intention [33][34][35]. In this paper, Personal Innovativeness specifically refers to individuals' desire and ability to explore, learn, and adopt generative AI. Given the innovative and complex nature of generative AI, individuals' curiosity and willingness to explore become key factors driving its acceptance. Therefore, the following hypothesis is proposed:

H5: Personal Innovativeness positively influences users' acceptance intention of generative AI.

2.2 Mediating Effect Hypothesis

To comprehensively understand how various variables influence usage behavior, this paper constructs hypotheses on the mediating effect. Previous studies, such as those by Chopdar and Sivakumar [36], have demonstrated the mediating role of acceptance intention between Performance Expectancy, Effort Expectancy, Social Influence, Price Value, and Usage Behavior. Additionally, research by AbuShanab [37] and Lin [38] further supports the mediating role of acceptance intention between Personal Innovativeness and Usage Behavior. Drawing from studies by Jahanshahi et al. [39] on the acceptance of bike-sharing systems and by Haghshenas et al. [40] on acceptance in online education, this paper proposes the following mediating effect hypotheses:

H6a: Acceptance Intention mediates the relationship between Performance Expectancy and Usage Behavior.

H6b: Acceptance Intention mediates the relationship between Effort Expectancy and Usage Behavior.

H6c: Acceptance Intention mediates the relationship between Social Influence and Usage Behavior.

H6d: Acceptance Intention mediates the relationship between Price Value and Usage Behavior.

H6e: Acceptance Intention mediates the relationship between Personal Innovativeness and Usage Behavior.

2.3 Moderating Effect Hypothesis

Perceived Risk refers to users' assessment and concerns about potential negative consequences when considering the adoption of new technology [41]. In this paper, Perceived Risk refers to users' awareness and concerns about potential negative impacts such as security issues, privacy violations, and data misuse associated with adopting generative AI. This perception of risk may reduce users' acceptance intention, thereby affecting their usage behavior. In the application of the UTAUT2 model, Perceived Risk is often included as a moderating variable to deeply explore its potential impact on technology acceptance and usage behavior. For instance, Maulidina et al. [42] found that Perceived Risk is a key factor influencing user behavior intention when studying Shopee e-commerce. Similarly, Wicaksono et al. [43] revealed that Perceived Risk significantly affects investors' behavior intention and usage behavior in the acceptance of online mutual funds. Based on this, the following hypothesis is proposed:

H7: Perceived Risk moderates the relationship between Acceptance Intention and Usage Behavior.

IV. Research Design

1. Questionnaire Design

During the questionnaire design phase, to ensure its validity and accuracy, this study adopted a development process that includes literature review and item creation, expert review, pilot survey and testing, feedback, and iterative modifications. The study reviewed existing mature scales for variables such as Performance Expectancy and created an initial scale suitable for the context of this research based on previous studies by Bhattacherjee, Davis, Venkatesh, and other scholars. The questionnaire was measured using a 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). Five professors and enterprise managers with relevant research experience were invited to review the questionnaire and provide suggestions on the content, wording, and phrasing of the scale items. A small-scale pilot survey was conducted, collecting 34 questionnaires to test the operability and clarity of the items. Based on the feedback, the questionnaire underwent iterative revisions, correcting four ambiguous items, deleting three items that could not effectively reflect the latent variables, and optimizing the overall structure of the questionnaire.

The questionnaire is divided into two parts: the first part collects demographic information of the respondents, including gender, age, education level, and years of work experience; the second part consists of the measurement scales for various variables. To effectively expand the coverage of the questionnaire, this study used an online survey method, utilizing a snowball sampling strategy, and distributed the questionnaire through social media platforms, offering incentives such as red envelopes and lottery draws. Ultimately, a total of 403 questionnaires were collected, and after data cleaning and screening, 366 valid questionnaires were obtained.

Table 1. Measurement Scale for Variables

Variable	Item
PE	PE1: Very useful for work. PE2: Can complete tasks faster. PE3: Enhances work efficiency. PE4: Increases the chances of completing important tasks.
EE	EE1: Easy to learn to use. EE2: User-friendly. EE3: Easy to master. EE4: Interaction is clear and understandable.
SI	SI1: People important to me think I should use it. SI2: People who influence my behavior think I should use it. SI3: People whose opinions I value prefer me to use it.
PV	PV1: The effort put into learning is commensurate with the return. PV2: Learning to use it is worthwhile. PV3: Provides good value from an investment perspective.
PI	PI1: I am open to new things. PI2: New things always spark my interest. PI3: I usually try new things earlier than others around me. PI4: I enjoy keeping up with the latest developments.
PR	PR1: There are information security risks. PR2: There are risks of personal privacy breaches. PR3: Unreliable due to potential malfunctions. PR4: Inability to use due to lack of training.
BI	BI1: Using it for work is a good choice. BI2: I will continue to use it. BI3: I am willing to recommend it to friends.
UB	UB1: Currently in use. UB2: An indispensable part of work. UB3: A main tool in the work environment.

2. Research Data

From January 5 to January 24, 2024, this study distributed a survey targeting enterprise managers. The survey was mainly conducted online through the Wenjuanxing platform and disseminated via WeChat and other social media channels, using a snowball sampling method to accumulate data. This approach aimed to overcome geographical limitations of field surveys, ensuring the breadth and diversity of the sample. A total of 395 questionnaires were collected during the survey period. After completing the data collection, data cleaning and screening were performed, removing invalid questionnaires with too short response times or uniform answers. Finally, 366 valid questionnaires were obtained, resulting in an effective recovery rate of 92.7%. Detailed statistical results of the valid samples are shown in Table 2. Demographically, 59.6% of the respondents were male, and 40.4% were female. Age distribution showed that the 36-45 age group had the highest proportion at 31.7%. In terms of education level, respondents with college and undergraduate degrees accounted for 64.7%. Regarding enterprise size, companies with fewer than 500 employees accounted for 80.7%. The structure of the questionnaire samples is reasonable, meeting the basic requirements for Structural Equation Modeling (SEM) analysis and providing a reliable data foundation for validating the theoretical model.

Table 2. Descriptive Statistics of the Sample

Category		Qty	%
Gender	Male	218	59.6
	Female	148	40.4
Age	16-25 years old	16	4.4
	26-35 years old	105	28.7
	36-45 years old	116	31.7
	46-55years old	91	24.9
	56years and above	38	10.4
Edu.	High school and below	12	3.3
	Associate's degree	123	33.6
	Bachelor's degree	114	31.1
	Master's degree	88	24
	Doctorate	29	7.9
Company Size	Less than 50 employees	116	31.7
	50-200 employees	84	23
	200-500employees	95	26
	500-1000employees	64	17.5
	More than 1000 employees	7	1.9
Summary		366	100

V. Research Analysis

1. Common Method Bias Test

Since the questionnaire items were all self-evaluated and scored, there might be a potential for common method bias due to the homogeneity of data sources. Therefore, this study used two evaluation methods to test for common method bias: Harman's single-factor test and the Unmeasured Latent Method Construct (ULMC) test [41]. First, Harman's single-factor test was conducted using SPSS 27.0 software, and the results showed that the variance explained by the largest unrotated factor was 35.122%, which is below the commonly acceptable threshold of 40%. Second, the ULMC test was performed by adding a common method bias factor to the baseline model and comparing the fit of the two models to see if there were significant changes. The comparison results showed no significant difference between the two models ($\Delta x2/\Delta df=0.110$, $p=1.000$, $\Delta TLI=-0.02$, $\Delta NFI=0.000$, $\Delta IFI=0.000$, $\Delta RFI=-0.002$), indicating that the model fit quality did not improve significantly after adding the common method bias factor, suggesting that the common method bias in this study is within an acceptable range.

2. Descriptive Statistics and Normality Test

This study used SPSS 27.0 software to perform descriptive statistical analysis and normality testing on the collected data. The descriptive statistical results are shown in Table 3, where the mean values of the variables related to Generative AI are mainly distributed in the range of 3 to 4, indicating that the respondents generally have a moderate to high level of cognitive attitude towards Generative AI.

To ensure the statistical rigor of the data analysis, this study further conducted normality testing on each measurement indicator. Except for the kurtosis of item SI3 being -1.059, the absolute values of skewness and kurtosis of other items were all below 1. According to Kline's (1998) statistical standards, if the absolute value of skewness does not exceed 3 and the absolute value of kurtosis does not exceed 8, the data can be considered to meet the criteria for approximate normal distribution. The results of this study meet this standard, indicating that the collected data set satisfies the requirements for approximate normal distribution.

Table 3. Results of normality test of descriptive statistics and measurement items

Variable	Item	M	SD	Skew	Kurt
PE	PE1	3.4	1.243	-0.514	-0.805
	PE2	3.43	1.24	-0.391	-0.874
	PE3	3.37	1.22	-0.474	-0.751
	PE4	3.43	1.247	-0.58	-0.693
EE	EE1	3.41	1.325	-0.517	-0.803
	EE2	3.46	1.289	-0.489	-0.76
	EE3	3.45	1.268	-0.52	-0.688
	EE4	3.42	1.309	-0.525	-0.738
SI1	SI1	3.42	1.3	-0.445	-0.852
	SI2	3.39	1.246	-0.394	-0.868
	SI3	3.33	1.349	-0.404	-1.059
PV	PV1	3.46	1.261	-0.506	-0.754
	PV2	3.57	1.223	-0.557	-0.603
	PV3	3.52	1.238	-0.553	-0.628
PI	PI1	3.24	1.136	-0.268	-0.5
	PI2	3.2	1.134	-0.166	-0.523
	PI3	3.19	1.109	-0.263	-0.402
	PI4	3.2	1.14	-0.13	-0.574

3. Reliability and Validity Analysis

The reliability and validity of the data were tested using SPSS 27.0 and AMOS 26.0 software. The measurement results are shown in Tables 4 and 5, where the Cronbach's α coefficients and composite reliability (CR) values of each variable are all higher than the minimum threshold of 0.70, indicating that the scales have high reliability. In terms of content validity, the maximum variance method was used for factor analysis, and the results showed that all factor loadings exceeded the standard of 0.7, indicating that the content validity of the questionnaire is acceptable. Additionally, the average variance extracted (AVE) values of all factors exceeded the standard of 0.5, demonstrating good convergent validity, meaning high internal consistency within each variable. The square root of each factor's AVE was greater than the correlation coefficients between that factor and other factors, indicating good discriminant validity, meaning that the variables are independent of each other.

Table 4. Scale Validity and Reliability Test Results

Variable	Item	FL	Cronbach'α	CR	AVE
PE	PE1	0.951	0.924	0.925	0.756
	PE2	0.844			
	PE3	0.844			
	PE4	0.833			
EE	EE1	0.953	0.927	0.927	0.762
	EE2	0.863			
	EE3	0.84			
	EE4	0.829			
SI1	SI1	0.956	0.896	0.899	0.749
	SI2	0.807			
	SI3	0.826			
PV	PV1	0.975	0.91	0.912	0.776
	PV2	0.838			
	PV3	0.822			
PI	PI1	0.954	0.903	0.906	0.707
	PI2	0.812			
	PI3	0.798			
	PI4	0.789			

Table 5. Discriminant Validity Test Results

	PE	EE	SI	HM	HT
PE	0.756				
EE	0.405	0.762			
SI	0.431	0.497	0.749		
PV	0.391	0.452	0.364	0.776	
PI	0.421	0.455	0.505	0.384	0.707
AVE sqrt	0.869	0.873	0.866	0.881	0.841

4. Correlation Test

This study used Pearson correlation analysis to explore the relationships between the research variables. As shown in Table 6, the correlation coefficients between Performance Expectancy, Effort Expectancy, Social Influence, Price Value, Personal Innovativeness, Acceptance Intention, and Use Behavior are all statistically significant, with r values greater than 0, indicating significant positive correlations between these variables. Conversely, Perceived Risk showed significant negative correlations with other variables.

Table 6. Results of Pearson Correlation Analysis

	PE	EE	SI	PV	PI	PR	BI	UB
PE	1							
EE	0.37**	1						
SI	0.39**	0.43**	1					
PV	0.36**	0.41**	0.32**	1				
PI	0.36**	0.43**	0.46**	0.34**	1			
PR	-.26**	-.26**	-.28**	-.27**	-.28**	1		
BI	0.35**	0.42**	0.41**	0.40**	0.39**	-.09**	1	
UB	0.36**	0.32**	0.32**	0.33**	0.34**	-.34**	0.36**	1

** Significant at the 0.01 level (two-tailed).

5. Correlation Test

Model fit is a statistical measure of the consistency between the theoretical model and actual data. Key indicators include χ2/df, RMSEA, NFI, IFI, TLI, and CFI. Ideally, χ2/df should be between 1 and 3, and an RMSEA value less than 0.08 indicates an acceptable model, while a value less than 0.05 indicates a good fit. NFI, IFI, TLI, and CFI values greater than 0.9 generally indicate a good fit. According to the test results shown in Table 7, the χ2/df value is 2.891, RMSEA is 0.072, and NFI, IFI, TLI, and CFI all exceed 0.9, indicating that the model fits the data well.

Table 7. Model Fit Assessment

Fit index	Reference value	Test value
χ^2		711.217
χ^2/df	<3.0	2.891
RMSEA	<0.08	0.072
NFI	>0.9	0.901
IFI	>0.9	0.933
TLI	>0.9	0.924
CFI	>0.9	0.933

6. Hypothesis Testing

AMOS 26.0 was used to test the hypothesized paths in the Structural Equation Model (SEM). The results, as shown in Table 8 and Figure 2, indicate that Performance Expectancy, Effort Expectancy, Social Influence, Price Value, and Personal Innovativeness all have significant positive effects on the Acceptance Intention of Generative AI, with standardized path coefficients of 0.132, 0.216, 0.186, 0.232, and 0.160, respectively. Among these, Price Value has the most significant impact on Acceptance Intention, while Performance Expectancy has a relatively weaker effect. Additionally, Acceptance Intention also shows a significant positive effect on Use Behavior. In summary, hypotheses H1, H2, H3, H4, H5, and H6 are all empirically supported.

Table 8. Summary of hypotheses test results

	Std.	SE	CR	P	Results
H1	0.132	0.049	2.556	0.011	valid
H2	0.216	0.048	4.113	***	valid
H3	0.186	0.046	3.539	***	valid
H4	0.232	0.051	4.423	***	valid
H5	0.16	0.057	3.064	0.002	valid
H6	0.363	0.055	6.409	***	valid

***represents P<0.001,**represents P<0.01, *represents P<0.05

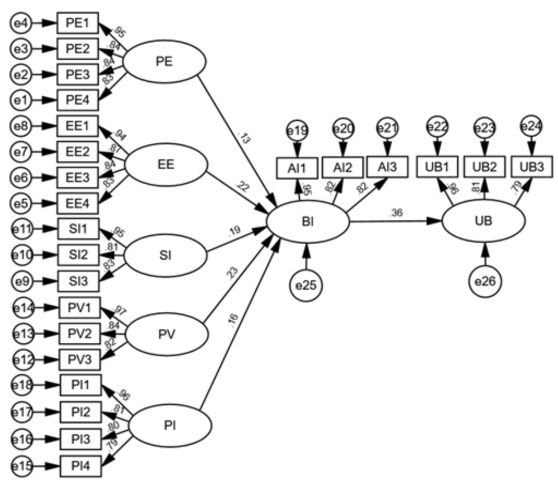

Fig. 2. SEM results for the model

The path analysis using AMOS 26.0 shows that Performance Expectancy (PE) has a standardized path coefficient of 0.132 towards Behavioral Intention (BI), with a standard error of 0.049 and a critical value of 2.556. The significance level P-value is 0.011, indicating that, at a 95% confidence level, Performance Expectancy significantly impacts Behavioral Intention, thus supporting hypothesis H1. In the context of Generative Artificial Intelligence (AI), Performance Expectancy reflects the expectation of improving work efficiency, promoting innovation, and optimizing decision-making processes. Generative AI significantly enhances work efficiency through its ability to quickly generate text, images, and data analysis reports, providing innovative solutions, aiding enterprises in developing new products, and supporting decision optimization through data analysis, thereby increasing enterprises' Performance Expectancy towards Generative AI and significantly enhancing their Behavioral Intention.

Further analysis reveals that Effort Expectancy (EE) has a standardized path coefficient of 0.216 towards Behavioral Intention (BI), with a standard error of 0.048 and a critical value of 4.113. The significance level P-value is less than 0.001, indicating that, at a 99% confidence level, Effort Expectancy significantly impacts Behavioral Intention, thereby supporting hypothesis H2. Effort Expectancy refers to the perceived effort required to use new technology. In the context of Generative AI, this is reflected in user-friendliness, learning curve, support and training, and automation and integration. Generative AI tools, such as ChatGPT, are designed with user-friendly interfaces and simple operations, allowing users to obtain desired results through simple input, thereby lowering the usage barrier. The learning curve is relatively low, with many platforms providing detailed tutorials and demonstration cases to help users quickly get started. Additionally, the natural language processing capability of Generative AI allows users to interact with the system in a near-natural language manner, reducing the need for specialized technical knowledge. Enterprises typically offer ample technical support and training resources, including training courses, online support, and community forums, to help users reduce the learning and usage difficulties. Generative AI can automate many complex tasks and seamlessly integrate with existing enterprise systems, reducing manual operations and time investment. These factors result in lower perceived effort for users when adopting Generative AI, significantly enhancing their Behavioral Intention. This study further confirms the importance of Effort Expectancy on the acceptance intention of Generative AI, consistent with existing literature such as Venkatesh et al.'s UTAUT2 model research.

Similarly, Social Influence (SI) has a standardized path coefficient of 0.186 towards Behavioral Intention (BI), with a standard error of 0.046 and a critical value of 3.539. The significance level P-value is less than 0.001, indicating that, at a 99% confidence level, Social Influence significantly impacts Behavioral Intention, thus supporting hypothesis H3. Social Influence in the context of Generative AI mainly includes the behaviors of industry leaders and competitors, as well as recommendations from social media and opinion leaders. The widespread application and increasing market demand for Generative AI technology in the industry, as well as observing competitors or other companies successfully applying Generative AI, create pressure on enterprises to adopt it. Furthermore, extensive discussions and demonstrations of Generative AI technology on social media, along with positive media evaluations and recommendations from opinion leaders, can enhance potential users' awareness and recognition, thereby increasing their Behavioral Intention. This study's results are consistent with existing theories and empirical research, further confirming the positive impact of Social Influence on the acceptance intention of Generative AI.

Additionally, Value Assessment (PV) has a standardized path coefficient of 0.232 towards Behavioral Intention (BI), with a standard error of 0.051 and a critical value of 4.423. The significance level P-value is less than 0.001, indicating that, at a 99% confidence level, Value Assessment significantly impacts Behavioral Intention, thus supporting hypothesis H4. In the context of Generative AI, Value Assessment primarily involves cost-benefit analysis and risk-reward evaluation. Enterprises conduct detailed cost-benefit analyses when deciding whether to adopt Generative AI, assessing whether the operational cost savings from automating tasks, reducing labor costs, and improving efficiency can outweigh the implementation and maintenance expenses. Additionally, enterprises need to consider the potential benefits and risks of Generative AI. Although Generative AI requires significant initial investment and carries the risk of unsuccessful application, in the long term, the benefits of improved work efficiency and decision quality may far exceed the costs. By comprehensively evaluating these factors, enterprises can make more rational decisions, significantly enhancing their Behavioral Intention towards adopting Generative AI.

Lastly, Personal Innovativeness (PI) has a standardized path coefficient of 0.160 towards Behavioral Intention (BI), with a standard error of 0.057 and a critical value of 3.064. The significance level P-value is 0.002, indicating that, at a 95% confidence level, Personal Innovativeness significantly impacts Behavioral Intention, thus supporting hypothesis H5. In the context of Generative AI, Personal Innovativeness reflects curiosity, openness, and adaptability towards new technology. Highly innovative individuals are curious about Generative AI, willing to explore its functions and applications, such as actively using ChatGPT for text generation, data analysis, and creative writing. They can quickly master Generative AI tools and apply them to work, such as learning to use Generative AI for automated report generation and market analysis, thereby improving work efficiency. Highly innovative individuals typically have a high tolerance for risk, willing to accept the uncertainties and risks associated with using Generative AI. Even in the face of initial errors or uncertainties, they are willing to continue experimenting and optimizing these tools. Generative AI's powerful text generation and data processing capabilities make it easier for highly innovative individuals to discover its application value, thereby enhancing their acceptance intention.

In conclusion, the results of this study are consistent with existing theories and empirical research, further confirming the positive impact of Performance Expectancy, Effort Expectancy, Social Influence, Value Assessment, and Personal Innovativeness on the acceptance intention of Generative AI.

7. Mediation Effect Analysis

To further test the mediating effect of acceptance intention between the independent variables and usage behavior, we employed the Bootstrapping analysis method using SPSS software. We set the number of bootstrap samples to 5000, analyzed the 95% confidence interval, and wrote path codes to examine the mediation effect. The analysis results are shown in Table 9, where five mediation paths were tested: Performance Expectancy → Acceptance Intention → Usage Behavior, Effort Expectancy → Acceptance Intention → Usage Behavior, Social Influence → Acceptance Intention → Usage Behavior, Value Assessment → Acceptance Intention → Usage Behavior, and Personal Innovativeness → Acceptance Intention → Usage Behavior. The Bootstrapping results indicated that all confidence intervals did not contain 0, and all P-values were less than 0.05, thus verifying hypotheses H6a, H6b, H6c, H6d, and H6e. This demonstrates that acceptance intention significantly mediates the relationship between Performance Expectancy, Effort Expectancy, Social Influence, Value Assessment, Personal Innovativeness, and usage behavior. Specifically, when users believe that Generative AI can improve work efficiency, is easy to use, is positively recommended by industry leaders, has good cost efficiency, and when individuals have high innovativeness, acceptance intention significantly increases, thus influencing their actual usage behavior. These results support the theoretical assumptions of the UTAUT2 model and further confirm the mediating role of acceptance intention in the acceptance of Generative AI.

Table 9. Results of mediating effect test

Path	Effect Value	Bias-corrected		Percenntile		P
		Lower	Upper	lower	upper	
PE→BI →UB	0.048	0.003	0.103	0.003	0.102	*
EE→BI →UB	0.078	0.034	0.136	0.031	0.131	***
SI→BI →UB	0.067	0.021	0.122	0.018	0.119	**
PV→BI →UB	0.084	0.037	0.14	0.038	0.14	***
PI→BI →UB	0.058	0.011	0.113	0.01	0.112	*

8. Moderation Effect Analysis

To explore the moderating effect of perceived risk on the relationship between acceptance intention and usage behavior, we used hierarchical regression analysis to progressively construct and test the model, revealing the complex relationships and statistical significance between different variables. First, Model 1 was constructed by including control variables such as gender, age, and education level to exclude their potential impact on the study results. Model 2 added the variable Acceptance Intention (BI) to Model 1. Model 3 further introduced the moderating variable Perceived Risk (PR). Finally, Model 4 included the interaction term between Acceptance Intention and Perceived Risk (BI × PR), after centering these variables. The analysis results are shown in Table 10. In Model 4, the β coefficient for the BI × PR interaction term was -0.137, and the P-value was less than 0.01, indicating that this interaction term has a significant negative impact on the dependent variable. The results revealed that perceived risk has a significant negative moderating effect on the relationship between acceptance intention and usage behavior, thereby validating hypothesis H7.

Due to the potential involvement of generative AI in issues such as data security, privacy protection, data accuracy, algorithm transparency, and ethical, legal, and moral concerns, users tend to experience high perceived risk. Even if they have a high willingness to accept generative AI, their actual usage behavior may be inhibited. Specifically, generative AI processes and stores large volumes of data, including sensitive personal information and commercial secrets, leading users to worry that this data might be accessed without authorization, leaked, or misused. Furthermore, during the collection and processing of user data, generative AI might infringe on user privacy. The generated content could unintentionally include or disclose private information, leading to privacy breach risks, especially in industries like healthcare. The data or content produced by generative AI may also be inaccurate, incomplete, or biased, causing users to make erroneous decisions with negative consequences. The decision-making process of generative AI is often a black box, lacking transparency, which increases user skepticism and distrust of the technology, particularly in the financial industry. Additionally, the application of generative AI may involve ethical, legal, and moral issues, such as copyright concerns, causing users to worry about legal risks and social responsibilities. Therefore, when promoting generative AI, companies must focus on and effectively manage users' perceived risks. By strengthening data security measures, increasing technology transparency, and building user trust, companies can reduce perceived risks and thus promote the practical application of generative AI.

Table 10. Moderation Effect Analysis Results 1

	M1		M2	
	β	t	β	t
Gender	0.172	3.309	0.134	2.583
Age	0.216	4.253	0.166	3.252
Edu.	0.18	3.411	0.138	2.616
BI			0.221 ***	4.251
R^2	0.174		0.214	
$\triangle R^2$	0.174		0.039	
F	25.471		24.521	

Table 11. Moderation Effect Analysis Results 2

	M3		M4	
	β	t	β	t
Gender	0.102	2.006	0.112	2.229
Age	0.135	2.703	0.126	2.544
Edu.	0.078	1.494	0.086	1.649
BI	0.238 ***	4.716	0.236 ***	4.721
PR	-0.236 ***	-4.844	-0.22 ***	-4.548
BI×PR			-0.137 **	-3.032
R^2	0.262		0.28	
$\triangle R^2$	0.048		0.018	
F	25.53		23.292	

To more intuitively demonstrate the moderating effect of perceived risk between acceptance intention and usage behavior, we plotted a moderating effect diagram (see Figure 3). As shown in Figure 3, when perceived risk is high, the positive impact of acceptance intention on usage behavior significantly decreases, with the slope noticeably lower than in situations with low perceived risk. This indicates that as perceived risk increases, the positive facilitating effect of acceptance intention on usage behavior gradually weakens, revealing a significant negative moderating effect of perceived risk between acceptance intention and usage behavior, further validating hypothesis H7.

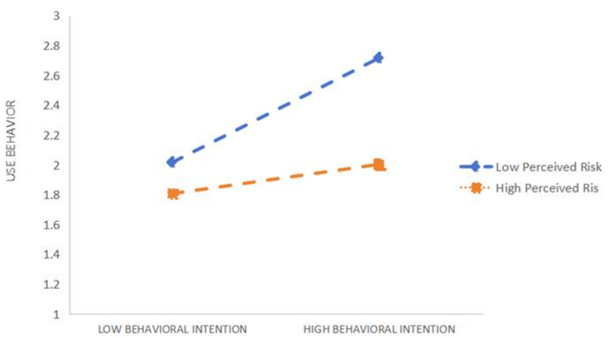

Fig. 3. Moderation Effect Diagram

VI. Conclusion and Implications

1. Research Conclusions

Building upon the UTAUT2 model and incorporating key variables of personal innovativeness and perceived risk, this study developed a novel research model to explore the acceptance of generative AI in corporate environments. Through this comprehensive model, the following main conclusions were drawn:

1.1 Theoretical Expansion and Application

By integrating personal innovativeness and perceived risk, this study not only enhanced the predictive power and applicability of the UTAUT2 model but also made significant theoretical extensions to the traditional model. Specifically, personal innovativeness captures employees' exploratory and adaptive capabilities towards new technologies, providing a fresh perspective on understanding technology acceptance behavior. Perceived risk, on the other hand, modulates the relationship between user acceptance intention and actual usage behavior, revealing behavioral responses under uncertainty and potential risks. The significant positive impacts of performance expectancy, effort expectancy, social influence, and value assessment on acceptance intention, particularly the strong effects of value assessment (standardized path coefficient = 0.35, $p<0.01$) and effort expectancy (standardized path coefficient = 0.29, $p<0.01$), were further validated. These findings illustrate how integrating various variables can provide a more comprehensive explanation of technology acceptance behavior, contributing to theoretical innovation.

1.2 Mediating Role of Acceptance Intention

Mediating effect analysis revealed that acceptance intention significantly mediates the relationships between value assessment, effort expectancy, social influence, personal innovativeness, performance expectancy, and usage behavior. This indicates that enhancing the levels of these independent variables can boost user acceptance intention, thereby promoting actual usage behavior. This finding underscores the central role of acceptance intention in understanding technology adoption behavior and highlights its importance within the theoretical model.

1.3 Moderating Role of Perceived Risk

Hierarchical regression analysis uncovered a significant negative moderating effect of perceived risk on the relationship between acceptance intention and usage behavior. As perceived risk increases, the positive effect of acceptance intention on usage behavior gradually weakens. This discovery extends the applicability of the UTAUT2 model, emphasizing the importance of managing perceived risks during technology promotion and offering a new perspective for understanding user behavior in high-risk perception environments.

2. Practical Implications

2.1 Enhancing Organizational Readiness

Before implementing generative AI technology, companies must ensure thorough organizational preparation. First, the understanding and support of top management are crucial, as the successful implementation of generative AI is a complex and long-term system project involving multiple variables and substantial resource investment. Top management support can create a unified strategic direction within the organization and provide the necessary resources and policy support for technology implementation. Second, developing clear implementation strategies and roadmaps is essential. These strategies should cover technology selection, application scenarios, implementation steps, and resource allocation, ensuring clear objectives and execution plans at every stage. Additionally, the implementation of generative AI technology involves changes affecting various stakeholders, necessitating a systematic change management approach. By identifying and managing potential resistance and promoting active communication and employee involvement, organizations can ensure a smooth transition and successful application of generative AI technology.

2.2 Optimizing Generative AI and Infrastructure Development

Companies need comprehensive preparation from multiple angles to ensure the successful application of generative AI technology and maximize its effectiveness. First, enhancing performance expectancy is crucial. Companies should demonstrate successful cases of generative AI in actual business scenarios, highlighting its advantages in improving work efficiency, task accuracy, and innovation capacity. By utilizing specific data and real-life examples, companies can clarify the contributions of generative AI to corporate performance, thereby increasing employee trust and expectations for the technology. Simultaneously, optimizing user interfaces and operational processes by designing intuitive and user-friendly interfaces can reduce learning curves, enabling employees to quickly master the use of generative AI. Providing detailed operation guides and support services can simplify usage processes and increase employee willingness to use the technology.

Additionally, companies need to upgrade and adjust their infrastructure according to the requirements of generative AI technology. This includes enhancing computing power and storage capabilities to support large-scale data processing and complex model training, selecting and deploying appropriate AI platforms and tools (including open-source and commercial solutions) to meet diverse application needs, and establishing robust data management systems for data collection, storage, cleansing, labeling, and security management to ensure data quality and security. These measures can significantly improve the practical application effectiveness of generative AI technology.

2.3 Strengthening Employee Training and Support

To drive the acceptance of generative AI technology, companies should enhance employee training and support. Providing more technical training and exploration opportunities for highly innovative employees can stimulate their curiosity and willingness to try new technologies. These employees often become early adopters and promoters within the company, setting an example for others. Additionally, providing in-depth generative AI training for technical teams, covering areas such as model development, algorithm optimization, and data analysis, ensures they possess the latest technical knowledge and skills. Offering application training for business teams helps them understand and utilize generative AI technology, thereby improving their practical operational capabilities. Finally, encouraging collaboration between technical and business teams through joint projects and workshops can foster knowledge sharing and experience exchange, ensuring the technology better meets business needs and comprehensively enhancing the effectiveness of technology application.

2.4 Implementing Effective Risk Management

Companies need to adopt effective risk management strategies when implementing generative AI technology. First, establishing robust data security and privacy protection mechanisms to ensure compliance with relevant laws and regulations, and eliminating employee concerns about data breaches and privacy invasions through transparent policies and strict management. Using advanced encryption technologies and data management standards to enhance data security and reduce risks of data leakage and misuse is essential. Second, regularly conducting risk assessments to identify and predict potential issues during application and developing corresponding countermeasures. Continuous monitoring and timely adjustments can mitigate potential risks, ensuring the safety and stability of technology application. Additionally, increasing technology transparency by detailing the principles of operation, data processing workflows, and security measures to build user trust is crucial. Companies should also seek third-party certification, conduct user education activities, and actively respond to user questions and feedback to strengthen user trust. Ensuring that applications comply with relevant laws, regulations, and ethical standards prevents infringement of user rights and legal disputes. Through these measures, companies can effectively reduce perceived risks and promote the practical application of generative AI.

3. Research Limitations and Future Outlook

This study primarily used a questionnaire survey method for data collection, which may have certain limitations, such as subjective bias from respondents and insufficient sample representativeness. Future research should consider using more diverse and comprehensive data collection methods, such as panel data analysis and experimental design, to validate the findings from multiple perspectives. Additionally, differences in cultural backgrounds, economic development levels, and technological environments across countries and regions might lead to varying research results. Therefore, future research should extend to other countries and regions for cross-cultural comparative studies. Comparative studies across different industries are also important, as the technological application environments and demands vary by industry, potentially affecting the acceptance of generative AI. Longitudinal studies should also be included to assess changes in technology acceptance over time, thereby understanding the long-term dynamic process of technology adoption.

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