International Journal of Innovative Research and Scientific Studies, 8(1) 2025, pages: 2021-2033

IJIRSS International Journal of Innovative Research & Scientific Studies

ISSN: 2617-6548

URL: www.ijirss.com

Impact of generative AI service adoption intent on user attitudes: Focusing on the Unified Theory of Acceptance and Use of Technology

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Abstract

The popularization of generative AI has led to significant social and industrial changes globally. As generative AI technology rapidly evolves, its influence is expected to grow, increasing the need for research on its acceptance and use. This study empirically analyzes the relationship between user attitudes and the adoption intent of generative AI services, offering insights into their utilization. Based on the Unified Theory of Acceptance and Use of Technology (UTAUT), four factors—Performance Expectancy, Effort Expectancy, Facilitating Conditions, and Hedonic Motivation—were identified as components of adoption intent. Additionally, this study analyzed the causal relationship between these factors and user attitudes, mediated by users' perceived emotional and functional values. A structural equation model was constructed with data from 356 users of generative AI services in South Korea. The analysis revealed that Performance Expectancy and Facilitating Conditions influence user attitudes through emotional and functional value mediation. Effort Expectancy significantly affected functional value, while Hedonic Motivation influenced emotional value, both exhibiting mediating effects. Emotional value had a greater impact on user attitudes than functional value. These findings suggest that emotional experiences are critical in the adoption of generative AI services, highlighting the need for strategies to enhance user engagement and satisfaction.

Keywords: Effort expectancy, Facilitating conditions, Generative AI, Hedonic motivation, Performance expectancy.

DOI: 10.53894/ijirss.v8i1.4874
Funding: This paper is written with support for research funding from aSSIST University.
History: Received: 3 January 2025/**Revised:** 6 February 2025/**Accepted:** 13 February 2025/**Published:** 21 February 2025

Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: All authors contributed equally to the conception and design of the study. All authors have read and agreed to the published version of the manuscript.
Transparency: The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.
Institutional Review Board Statement: The Research Ethics Committee of aSSIST University, South Korea, has granted approval for this study on 14 Nov. 2024 (Ref. No. The Statistics Act No. 33, 34).
Publisher: Innovative Research Publishing

1. Introduction

Since the introduction of OpenAI's ChatGPT in 2022, the widespread adoption of generative AI services has impacted not only daily life but also various industrial and business activities. Generative AI refers to artificial intelligence technology that actively generates outputs based on specific user requirements, learning from input data and producing new data outputs based on this learning [1]. Currently, generative AI is being widely applied across various fields, including tasks traditionally within the human domain, such as sentence composition, natural language processing, and creating images and videos [2]. Moreover, it has rapidly advanced beyond traditional AI technologies, demonstrating the ability to independently search for and learn from data to respond to user queries or tasks, actively generating outputs based on these processes [3].

After OpenAI's ChatGPT disrupted the market, Microsoft partnered with OpenAI to launch GPT-5. Google followed the release of its Bard model with Gemini, a next-generation multimodal AI capable of understanding not just text but also images, videos, and audio, as well as solving math problems and reasoning tasks. Meta released LLaMA 2, an open-source large language model accessible to everyone, integrating it with social media and advertising platforms [4, 5]. Additionally, image-generating AI services such as Novel AI, Midjourney, and Adobe Firefly have gained attention, alongside generative AI services for music and video creation. With big tech firms, IT giants, and startups all developing and launching generative AI services, the market for these technologies is growing rapidly [6, 7].

According to a survey by Emarketer [8] the growth rate of generative AI users among U.S. internet users remains strong at 28.6%. The report also predicts that by 2026, 40.6% of users will be utilizing generative AI. Ultimately, generative AI services are becoming complementary tools for consumers and businesses, enhancing a wide range of applications, productivity, and creativity while reshaping the entire digital ecosystem. Consequently, generative AI technologies designed for corporate workflows and systems, as well as general users, will continue to evolve, with user adoption rates expected to rise steadily.

According to the World Bank Group [9], the global generative AI market size is estimated at USD 10.14 billion, with projections suggesting it will grow to USD 1.3 trillion (approximately 1,706 trillion KRW) by 2032. McKinsey [10] projected that generative AI could add between USD 2.6 trillion and USD 4.4 trillion in annual economic value. Furthermore, the overall impact of artificial intelligence is expected to increase from 15% to 40%. As generative AI becomes increasingly important at individual and societal levels, major countries are expanding AI-related budgets, encouraging private investment, and fostering talent to secure competitiveness in an AI-driven society. Additionally, the emergence of generative AI is transforming education and industry, with its application in workplaces steadily increasing, further solidifying its importance across all aspects of life [11]. In light of the rapid development of generative AI, there is an emphasis on the need for users to develop the knowledge and critical capacity to use generative AI responsibly and effectively. Correspondingly, in response to the growing use of generative AI, in-depth discussions are ongoing regarding the skills and technical characteristics required to maximize its utility [12].

However, most previous studies have been based on Davis, et al. [13] Technology Acceptance Model [14]. Existing generative AI studies based on TAM mainly applied TAM variables to the field of generative AI, focusing on this level of analysis. While meaningful in verifying how the technological characteristics of generative AI influence perceived usefulness, ease of use, and adoption intent, these studies are limited in their failure to examine user-related factors that could impact acceptance. Moreover, while previous studies on generative AI services, particularly those focused on ChatGPT, have validated TAM as a robust model for explaining the adoption process of new technologies and services, few have integrated individual and technological characteristics into their analyses.

Against this backdrop, this study aimed to discuss the acceptance and usability of generative AI by incorporating both technological and individual factors into an expanded TAM. To achieve this, based on the Unified Theory of Acceptance and Use of Technology (UTAUT) proposed by Venkatesh, et al. [15], this study sought to examine the relationship between users' perceived functional and emotional values and their attitudes toward generative AI service use. The findings provide strategic insights to facilitate user engagement and satisfaction by considering customer experiences and needs in the development and evolution of generative AI services. Ultimately, this study is significant in that it analyzes the acceptance of generative AI services not just from a technology adoption perspective based on effectiveness and efficiency but also from the perspective of personal usability, value, and attitudes rooted in user experiences.

2. Literature Review and Hypothesis Development

2.1. Unified Theory of Acceptance and Use of Technology

TAM is a model based on the Theory of Reasoned Action (TRA), which emphasizes rational human decision-making. TRA posits that humans, as rational beings, make choices to maximize positive outcomes and minimize negative ones when undertaking specific actions [16]. Based on this theory, Davis, et al. [13] argued that an individual's perceived beliefs influence their attitude toward new technologies, which in turn affects adoption intent, eventually leading to action. Accordingly, TAM defines that the easier and more convenient users perceive a technology or service to be, the more useful they find it, positively influencing their attitude and increasing adoption [17].

Previous studies have verified that perceived ease of use and perceived usefulness directly or indirectly influence users' intent to adopt new technologies or services [18-20]. However, TAM has been criticized for focusing exclusively on core variables such as perceived ease of use and perceived usefulness while neglecting the characteristics of new technologies or individual traits when analyzing behavioral intent [21]. Accordingly, expanded models exploring factors that influence existing variables have been proposed, and Davis later introduced the Extended Technology Acceptance Model (ETAM) to enhance the theory's explanatory power by including external variables [22, 23].

In this context, UTAUT was proposed by Venkatesh, et al. [24] to explain the key factors influencing technology acceptance and use. UTAUT integrates several models, including TAM, the Theory of Planned Behavior (TPB), and the Diffusion of Innovations Theory (DIT). It significantly improves the predictive power of technology acceptance through four key factors: performance expectancy, effort expectancy, social influence, and facilitating conditions.

First, performance expectancy refers to the belief that a specific technology will enhance a user's job performance. Venkatesh, et al. [24] defined performance expectancy as "the degree to which a user expects benefits from using a particular system." This factor is conceptually similar to perceived usefulness in TAM. Performance expectancy is one of the most influential factors affecting technology acceptance intent; the more users believe that technology will improve their work or personal outcomes, the more likely they are to adopt it Kabra, et al. [21]. Second, effort expectancy refers to a user's perception of the ease of learning and using a specific technology. This concept is similar to perceived ease of use in TAM, reflecting how little physical and mental effort is required to use the technology, and it serves as an important factor in technology acceptance [13]. Third, facilitating conditions refer to the presence of organizational and technical infrastructure that supports a user's ability to use a specific technology. Facilitating conditions ensure smoother technology acceptance by providing users with the resources and support necessary for technology use [23]. When users are provided with the necessary technical support and resources, they are more likely to use the technology [22]. Fourth, hedonic motivation refers to the enjoyment or interest users experience when using a technology Venkatesh, et al. [24]. Brown and Venkatesh [25] emphasized that enjoyment and positive emotions play a significant role in users' intent to accept technology, contributing to their voluntary use of the technology.

Since its introduction, researchers have studied the expanded TAM in various contexts. Particularly after 2010, as media technologies advanced rapidly, the model has been applied to studies on new media technologies such as the internet, smartphones, and the metaverse [26]. Additionally, following the launch of generative AI, studies have applied TAM to generative AI [27]. A study by Lambert and Stevens [28] showed that ChatGPT's technological affordances significantly influence Perceived Ease of Use and Perceived Usefulness and also affect the intention for continued use. Another study by Al-Mamary, et al. [29] found that openness, innovativeness, and self-efficacy have significant effects on attitudes toward ChatGPT and its usage intentions. Furthermore, Budhathoki, et al. [30] found that the four factors of UTAUT have a significant relationship with ChatGPT users' digital literacy and acceptance intentions.

2.2. Technology Acceptance and Perceived Value

In technology acceptance research, the perceived value significantly influences users' adoption intentions and behaviors. Zeithaml [31] defined perceived value as the overall assessment users make while utilizing a particular product or service. Perceived value is generally divided into emotional value and functional value, both of which play a critical role in determining how consumers evaluate technology in the context of technology acceptance [32-34]. Existing research on technology acceptance and perceived value has analyzed the diverse impacts of these concepts on user behavior. Agarwal and Prasad [35] argued that users' perceived usefulness and ease of use significantly influence IT adoption intentions, aligning with UTAUT's performance expectancy and effort expectancy. Additionally, Karahanna, et al. [36] emphasized that users consider the emotional and functional benefits of new technologies when deciding to adopt them.

Emotional value refers to the emotional benefits and enjoyment users experience while using technology. It plays an important role in technology usage experiences, where positive emotional feelings motivate continued use [37]. Emotional value encompasses elements such as fun, interest, and satisfaction during technology use. It relates to the emotional reactions or enjoyment consumers feel while using it. Research indicates that technologies that provide emotionally positive experiences can positively shape users' attitudes toward technology acceptance [15, 38]. Such positive emotions may promote continued technology use and enhance user loyalty [39]. According to Agarwal and Karahanna [40], emotional experiences with technology play a key role in users' technology acceptance. They found that when users experience positive emotions while using a technology, their intention to use it increases. Similarly, Van Der Heijden [41] studied the impact of positive emotional experiences on user attitudes in online shopping platforms and concluded that emotional value significantly influences users' attitudes and behaviors. Higher psychological satisfaction, enjoyment, and emotional connection from using technology tend to make users more inclined to adopt it [42].

When generative AI services deliver expected outcomes, such as personalized recommendations, creative task automation, or increased efficiency, these performance expectancies can evoke positive emotional reactions, leading users to assign higher emotional value to the technology. Studies suggest that performance expectancy plays a crucial role in enhancing the emotional value of technology [1]. When users expect high performance from generative AI services, it generates positive emotional responses toward the technology [15, 24]. Robust infrastructure, educational resources, and technical support for generative AI services help users have positive experiences while using the technology. When facilitating conditions are well-established, users experience less inconvenience or stress during technology use, contributing to the formation of positive emotional value [42]. When appropriate support and resources are provided, users are more likely to have positive emotional experiences during technology use [15, 21].

Additionally, if generative AI services help users enjoy creative tasks or generate interesting content, this can greatly enhance users' emotional value. Studies indicate that hedonic motivation, such as the enjoyment experienced during technology use, is closely linked to emotional value, which, in turn, positively affects users' adoption intentions [43]. Ultimately, users of generative AI services perceive emotional value in the technology acceptance process owing to factors such as performance expectancy, effort expectancy, facilitating conditions, and hedonic motivation. Accordingly, this study proposes the following hypotheses:

$H_{1:}$ Users' Performance expectancy regarding generative AI services has a positive effect on emotional value.
$H_{2:}$ Users' Effort expectancy regarding generative AI services has a positive effect on emotional value.
$H_{3:}$ Users' Facilitating conditions regarding generative AI services have a positive effect on emotional value.
$H_{4:}$ Users' Hedonic motivation regarding generative AI services has a positive effect on emotional value.

Functional value refers to the practical and useful benefits users gain from using technology. It is defined as an evaluation related to the actual usability, utility, and efficiency of a specific technology; higher functional value positively shapes users' attitudes toward technology acceptance [44]. The core of functional value lies in how useful the technology is or how much time and effort it can save [1]. Functional value is determined by whether the technology enhances users' work efficiency, solves problems, and provides tangible outcomes. Studies indicate that the greater the tangible benefits offered by technology, the more positively users' attitudes toward technology acceptance are shaped [13, 15].

Turel, et al. [45] analyzed the impact of IT services' functional value on user satisfaction and continued usage intention, showing that a higher functional value leads to more positive attitudes toward service acceptance. Furthermore, Han, et al. [46] evaluated functional value in terms of factors such as electric vehicles' driving range, charging speed, and reduced maintenance costs, arguing that when such factors are perceived as superior to those of internal combustion vehicles, functional value is rated higher, increasing adoption intention. This indicates that the more users value the utility of technology, the stronger their intent to adopt it becomes [34].

If users perceive that the learning curve for using generative AI services is low and the technology is easy to use, this can act as a factor that enhances functional value. This is because users believe that they can better enjoy the functional benefits provided by a technology when they feel it is easy to use [47]. When users believe they can easily learn to use generative AI services, they perceive higher functional value [13]. Additionally, as Yang, et al. [1] noted, when users expect technology services to enhance their work efficiency or produce better outcomes, they tend to evaluate the technology's functional value more highly. When AI is expected to generate text or perform data analysis more quickly and accurately, users will likely evaluate the technology's functional value positively [15].

Furthermore, users' enjoyment while using technology can also influence its functional value. Poushneh and Vasquez-Parraga [42] argued that if users enjoy creative thinking and problem-solving with generative AI services, this can positively impact the technology's functional value. These factors influence technology acceptance among generative AI service users and ultimately have a positive effect on their perception of functional value. Accordingly, this study proposes the following hypotheses:

$H_{5:}$ Users' performance expectancy regarding generative AI services has a positive effect on functional value.
$H_{6:}$ Users' effort expectancy regarding generative AI services has a positive effect on functional value.
$H_{7:}$ Users' facilitating conditions regarding generative AI services have a positive effect on functional value.
$H_{8:}$ Users' hedonic motivation regarding generative AI services has a positive effect on functional value.

2.3. Emotional Value, Functional Value, and Usage Attitude

Attitude refers to a mental disposition toward behavior, encompassing feelings of liking or disliking experienced in response to something [48]. Attitude is also defined as an intention directed toward a particular object or subject [49]. Usage attitude refers to the psychological response of an individual, encompassing cognition, emotion, and behavior when using a specific object [50]. Therefore, usage attitude plays a critical role in decision-making and influences satisfaction or dissatisfaction based on positive or negative evaluations after decisions are made [51].

Previous studies on technology service usage and attitudes have identified various determining factors. Zhu and Chang [52] analyzed consumer attitudes and intentions related to free trials of technology-based services and identified perceived usefulness, ease of use, risk, and social influence as major determinants. A study on the use of self-service technology in retail environments reported that perceived usefulness, ease of use, reliability, and enjoyment influence usage attitudes, which subsequently play a key role in predicting actual usage [53]. Additionally, Dar and Jan [54] analyzed students' usage and attitudes toward ICT in e-learning environments, explaining that ICT usage attitudes are influenced not solely by individual technical skills but also by the social environment, psychological traits, and technological characteristics. Kasilingam [55] demonstrated that in mobile online shopping, users' attitudes toward smartphone chatbot services are shaped by factors such as usefulness, ease of use, and enjoyment, while trust and innovativeness directly affect usage intentions.

Theotokis, et al. [56] emphasized the impact of customer–technology contact on usage attitudes, noting that users' attitudes are adjusted based on individual traits and readiness for technology acceptance. Pramatari and Theotokis [57] studied RFID-based services and highlighted that system characteristics and personal traits significantly influence usage attitudes, with performance expectancy and information privacy concerns playing key roles in attitude formation. Upadhyay, et al. [58] investigated key factors influencing sales professionals' attitudes toward sales technology, revealing that peer technology use and organizational support services directly impact technology adoption, with perceived usefulness identified as a critical factor shaping attitudes toward technology use.

Among the various factors influencing usage attitudes, perceived value factors have been proposed to play an important role. Zolkepli, et al. [59] examined mobile app usage and found that functional, social, emotional, and conditional values significantly influence usage attitudes, while app evaluation and costs also have an impact. Zhou [60] analyzed the impact of perceived value on user acceptance behavior in mobile commerce, emphasizing the significant role of social value. Wang, et al. [61] revealed that TikTok users' perceived value positively influences social connectedness, with informational and social value playing key roles in fostering users' sense of belonging. Liu, et al. [62] suggested that in the context of AI voice assistants, usefulness, enjoyment, and emotional value can vary based on users' psychological factors such as loneliness and resistance to innovation. Additionally, in the context of AI-driven image-generation businesses, perceived customer value and social influence significantly impact user behavioral intentions, with user creativity having a notable effect on usage attitudes [63].

Among perceived value factors, numerous prior studies have confirmed emotional value and functional value as critical elements in determining users' behavioral intentions and attitudes. Bagozzi [64] extended TAM to analyze the influence of users' emotional responses on technology acceptance intentions, identifying emotional value as playing an important role in shaping attitudes. Kim, et al. [39] analyzed mobile service acceptance and confirmed that functional value significantly impacts users' acceptance intentions. Gefen, et al. [65] studied user satisfaction and reuse intention in online shopping malls and highlighted that functional value improves user experience, while emotional value strengthens user loyalty.

H_9: Users' emotional value regarding generative AI services has a positive effect on usage attitude.

H_{10}: Users' functional value regarding generative AI services has a positive effect on usage attitude.

3. Methods

3.1. Research Model

This study constructed a research model based on the hypotheses, as illustrated in Figure 1. The core acceptance determinants of UTAUT, proposed by Venkatesh, et al. [15], are performance expectancy, effort expectancy, facilitating conditions, and hedonic motivation. These determinants were structured to examine their impact on users' emotional and functional value, which mediates the usage attitude toward generative AI services. Ultimately, through structural equation modeling, this study derived the results of each path analysis and validated the mediating effects to analyze how the technology acceptance factors of generative AI service users influence their attitude toward service acceptance.

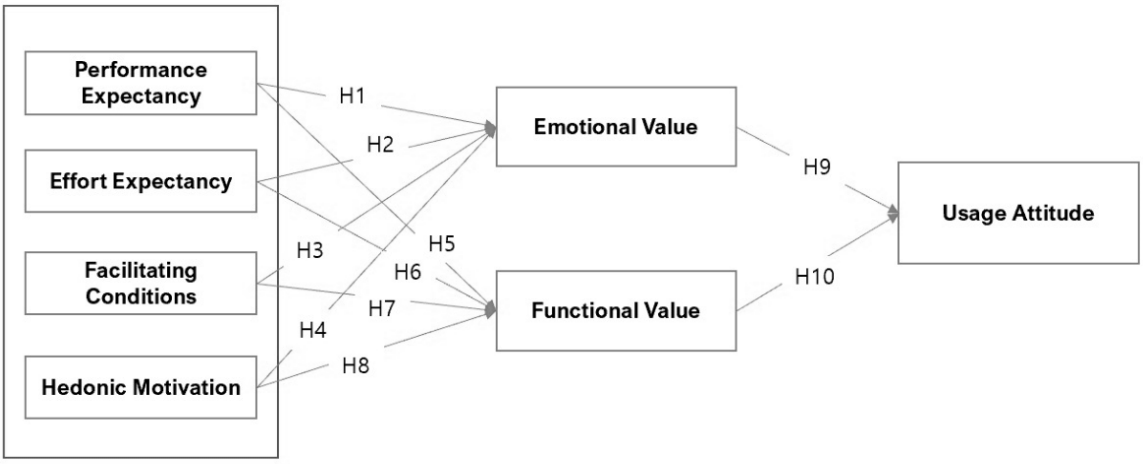

Figure 1.
Research model.

3.2. Measurement Variable and Data Collection

Survey items were developed based on prior research, and operational variables for each survey component were defined. First, the independent variables consisted of four factors. Performance expectancy refers to the perception that using generative AI services can benefit an individual's tasks. Effort expectancy was defined as the degree to which generative AI services are perceived as easy to use. Facilitating conditions indicate the perceived presence of organizational or technical infrastructure that supports the use of generative AI services. Hedonic motivation was defined as the fun or enjoyment users feel from using generative AI services.

The mediating variables included emotional value and functional value. Emotional value refers to the positive feelings and satisfaction perceived by users regarding the quality of generative AI services, ultimately influencing their acceptance attitude. Functional value refers to users' active engagement with and functional satisfaction in using generative AI services, defined as a variable that positively affects their attitude. Finally, the dependent variable, usage attitude, represents users' level of engagement and willingness to use generative AI services in various ways.

These defined variables comprised a total of 25 survey items, as summarized in Table 1. Survey data were analyzed using SPSS 27.0 to examine demographic characteristics, descriptive statistics, and exploratory factor analysis. Confirmatory factor analysis (CFA) and path analysis of the structural equation model were conducted using AMOS 27.0 to test the hypotheses.

Table 1.
Variable definitions and measurement items.

Factors	Measurement Items	References
Performance expectancy	• Generative AI services help complete tasks quickly. • Generative AI services help improve productivity in tasks. • The information or services provided by generative AI services are useful to me. • Generative AI services are convenient due to their personalized features.	Venkatesh, et al. [15] Venkatesh, et al. [24] Budhathoki, et al. [30]
Effort expectancy	• Generative AI services are easy to use. • The features of generative AI services are easy to control. • Generative AI services are flexibly used in various ways.	
Facilitating conditions	• I do not find it difficult to use generative AI services. • I tend to use generative AI services efficiently. • I am well aware of and can explain the features offered by generative AI services. • I do not require others' help when using generative AI services.	
Hedonic motivation	• Using generative AI services is enjoyable. • Generative AI services satisfy my curiosity. • Using generative AI services is fun.	
Emotional value	• Using generative AI services makes me feel good. • Generative AI services give me a sense of stability. • Using generative AI services feels familiar to me.	Kim, et al. [39]; Bagozzi [64] and Gefen, et al. [65]
Functional value	• I am satisfied with the quality of information gained through generative AI services. • I consistently receive quality information and responses from generative AI services. • I frequently use generative AI services to acquire information and knowledge.	Zolkepli, et al. [59]; Zhou [60] and Liu, et al. [62]
Usage attitude	• I have a positive attitude toward using generative AI services. • I actively intend to utilize generative AI services. • I intend to use generative AI services for various purposes.	Tiwari, et al. [51]

3.3. Demographic Information of the Data

For this study, an online survey was conducted targeting users of language-based generative AI services, such as OpenAI's ChatGPT, Google Bard, Microsoft Bing, and Meta LLaMA. The survey was conducted using self-reported questionnaires over a three-week period starting April 10, 2023. A total of 425 responses were collected, of which 69 were excluded due to insincere responses, leaving 356 valid responses for analysis. Insincere responses were identified using a post-hoc non-invasive method based on single-line responses and psychometric agreement consistency. A lack of agreement/disagreement consistency was classified as insincere if the correlation between individual responses to paired items was below 0.3, following the criteria proposed by Meade and Craig [66].

As shown in Table 2, the gender distribution of participants was nearly equal, with 51.4% male and 48.6% female. The age distribution was 21.3% in their 20s, 38.2% in their 30s, 25.8% in their 40s, and 14.6% in their 50s, showing a relatively balanced usage pattern. Regarding occupation, 64% were office workers, 7.3% were students, 14.4% were professionals, 5.3% were self-employed, and 9% fell into other categories, including homemakers and the unemployed. Regarding the frequency of generative AI usage, 7.6% used it daily, 15.4% used it at least three times a week, 34% used it at least once a week, 21.9% used it at least once a month, 6.2% used it at least once every 2–3 months, and 14.9% were one-time users. The most commonly used services were ChatGPT at 41.9%, followed by Google Bard and Microsoft Bing at 10.4%, Naver HyperCLOVA X at 9.8%, Kakao KoGPT at 7.2%, and Meta LLaMA at 3.3%. Additionally, 17.1% of respondents reported using various other generative AI services.

Table 2.
Demographic information of survey participants

Category		Frequency	Percentage (%)
Gender	Male	183	51.4
	Female	173	48.6
Total		356	100
Age	20s	76	21.3
	30s	136	38.2
	40s	92	25.8
	50s	52	14.6
Total		356	100
Occupation	Office worker	228	64.0

	Student	26	7.3
	Professional	51	14.4
	Self-employed	19	5.3
	Other	32	9
Total		356	100
Generative AI service usage frequency	Daily	27	7.6
	At least three times a week	55	15.4
	At least once a week	121	34.0
	At least once a month	78	21.9
	At least once every 2-3 months	22	6.2
	One-time user	53	14.9
Total		356	100
Primarily used generative AI service	ChatGPT	149	41.9
	Google Bard	37	10.4
	Meta LLaMA	12	3.3
	Microsoft Bing	37	10.4
	Naver HyperCLOVA	35	9.8
	Kakao KoGPT	26	7.2
	Other	61	17.1
Total		356	100

Note: *Professional category includes public servants, medical, finance, consulting, education, arts, information technology, and so on.

4. Results

4.1. Analysis Results of Reliability and Validity

As shown in Table 3, the analysis results for reliability and convergent validity of the measurement model were satisfactory. To address model fit and the issue of inflated estimation errors, the partial least squares method was applied [67]. Factor loadings ranged from 0.644 to 0.900, demonstrating good reliability. Internal consistency was confirmed with composite reliability values between 0.814 and 0.880. Statistical significance was ensured as t-values exceeded 6.5. The Average Variance Extracted (AVE) values were above 0.5, and Cronbach's α values ranged from 0.812 to 0.875, ensuring convergent validity. An analysis of the model fit of the structural equation measurement model showed $\chi^2(df) = 629.723$ and χ^2/degrees of freedom = 2.479. The Goodness-of-Fit Index (GFI) was 0.864, the Adjusted Goodness-of-Fit Index (AGFI) was 0.826, the Normal Fit Index (NFI) was 0.912, and the Root Mean Square Error of Approximation (RMSEA) was 0.068, indicating statistically significant model fit indices for the measurement model.

Table 3.
Results of reliability and convergent validity test

Variable	Measurement item	Standard loading	Standard error	t-value (p)	CR	AVE	Cronbach α
Performance expectancy	PE1	0.808			0.874	0.636	0.867
	PE1	0.867	0.063	17.545***			
	PE1	0.815	0.063	16.238***			
	PE1	0.688	0.067	13.076***			
Effort expectancy	EE1	0.873			0.865	0.682	0.865
	EE2	0.808	0.056	17.424***			
	EE3	0.794	0.053	16.987***			
Facilitating conditions	FC1	0.806			0.825	0.542	0.827
	FC2	0.745	0.070	13.790***			
	FC3	0.681	0.067	12.416***			
	FC4	0.708	0.073	12.991***			
Hedonic motivation	HM1	0.834			0.856	0.585	0.845
	HM 2	0.828	0.058	16.678***			
	HM 3	0.832	0.055	16.777***			
Emotional value	EV1	0.667			0.838	0.565	0.838
	EV2	0.736	0.104	11.509***			
	EV3	0.821	0.107	12.570***			
	EV4	0.775	0.106	12.011***			
Functional value	FV1	0.871			0.880	0.651	0.875
	FV 2	0.787	0.051	17.256***			

	FV 3	0.900	0.048	21.282***			
	FV 4	0.644	0.051	12.870***			
Usage attitude	UB1	0.697			0.814	0.594	0.812
	UB 2	0.780	0.100	12.196***			
	UB 3	0.829	0.099	12.705***			

Note: *** p<0.001

As shown in Table 4, CFA was conducted to determine whether the observed variables constituting each latent variable were validly constructed prior to conducting structural equation modeling analysis. The initial model includes all items, while the final model only includes the variables used in the actual structural equation modeling, showing the results accordingly. The model fit was evaluated based on established indices such as the Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), and RMSEA [68]. The final model showed better results than the initial model. Specifically, in the final model, TLI exceeded the threshold of 0.9, and CFI was also above the standard value of 0.9. The RMSEA was below the threshold of 0.10, and overall, the model showed a good fit, confirming that the CFA model was appropriate.

Table 4.
Fit indices for the measurement model.

Model	χ^2 (df)	p	χ^2/df	RMR	GFI	AGFI	NFI	TLI	CFI	RMSEA
Initial model	843.499	0	2.948	0.070	0.825	0.779	0.870	0.848	0.870	0.079
Final model	629.723	0	2.479	0.044	0.864	0.826	0.912	0.917	0.925	0.068

The square root of all variables' AVE values was greater than the correlations, indicating high discriminant validity. Based on this criterion, as shown in Table 5, the analysis of the AVE values and correlations among latent variables revealed that the square root of each latent variable's AVE was greater than the inter-variable correlations, thereby confirming discriminant validity.

Table 5.
Correlation matrix and AVE.

Variables	PE	EE	FC	HM	EV	FV	UA
Performance expectancy (PE)	0.826						
Effort expectancy (EE)	0.559**	0.797					
Facilitating conditions (FC)	0.695**	0.430**	0.736				
Hedonic motivation (HM)	0.466**	0.573**	0.439**	0.831			
Emotional value (EV)	0.501**	0.659**	0.430**	0.625**	0.752		
Functional value (FV)	0.404**	0.616**	0.335**	0.373**	0.603**	0.807	
Usage attitude (UA)	0.418**	0.585**	0.361**	0.493**	0.625**	0.557**	0.771

Note: ** p<0.01 / The square root of AVE is shown in bold letters.

4.2. Analysis Result of Structural Model

The structural model's fit indices analysis showed χ^2 (p) = 667.743 and χ^2/degrees of freedom = 2.578. GFI was 0.855, and NFI was 0.875, both indicating an acceptable fit. The Root Mean Square Residual (RMR) was 0.070, AGFI was 0.818, and RMSEA was 0.070, indicating significant fit values. TLI, which evaluates explanatory power, was 0.905, and CFI, which is robust to sample size, was 0.919, confirming the appropriateness of the basic model.

As shown in Table 6, path analysis was conducted to test the hypotheses, resulting in 7 out of 10 hypotheses being supported. Performance expectancy (6.536, p<0.001), facilitating conditions (3.630, p<0.01), and hedonic motivation (5.237, p<0.001) had a positive effect on emotional value. However, effort expectancy did not affect emotional value; therefore, the hypothesis was rejected. For functional value, performance expectancy (7.757, p<0.001) and facilitating conditions (5.610, p<0.05) had a positive effect. However, effort expectancy and hedonic motivation did not support the hypotheses. Emotional value (7.440, p<0.001) and functional value (4.786, p<0.001) both positively influenced usage attitude; therefore, the hypotheses were supported. Consequently, it was confirmed that emotional value is a more important factor than functional value in influencing users' usage attitude toward generative AI services.

Table 6.
Results of hypothesis test

	Hypothesis (Path)	Standardized regression weights	S.E.	CR(p)	Support
H1	Performance expectancy -> emotional value	0.205	0.043	4.786***	Supported
H2	Effort expectancy -> emotional value	0.001	0.096	0.009	Rejected
H3	Facilitating conditions -> emotional value	0.054	0.086	3.630**	Supported
H4	Hedonic motivation -> emotional value	0.253	0.048	5.237***	Supported
H5	Performance expectancy -> functional value	0.852	0.11	7.757***	Supported
H6	Effort expectancy -> functional value	-0.057	0.172	-0.331	Rejected
H7	Facilitating conditions -> functional value	0.086	0.154	5.610*	Supported
H8	Hedonic motivation -> functional value	-0.027	0.081	-0.336	Rejected
H9	Emotional value -> usage attitude	0.617	0.083	7.440***	Supported
H10	Functional value -> usage attitude	0.205	0.043	4.786***	Supported

Note: Structural Model Fit: χ^2(df) 667.743, χ^2/degree of freedom 2.578, RMS 0.047, GFI 0.855, AGFI 0.818, NFI 0.875, TLI 0.906, CFI 0.919, RMSEA 0.070 / Note: * p<0.05, ** p<0.01, *** p<0.001.

4.3. Analysis Result of Mediating Effects

The mediating effects of emotional and functional value in the influence of performance expectancy, effort expectancy, facilitating conditions, and hedonic motivation, which are key acceptance factors of generative AI services, on usage attitude were tested using the Sobel Test (Table 7). The results showed that performance expectancy and facilitating conditions influenced usage attitude through both emotional and functional values. However, hedonic motivation only acted as a mediator through emotional value. Conversely, effort expectancy did not show a mediating effect through either emotional or functional value on usage attitude. These results indicate that for generative AI service users, effort expectancy related to ease and convenience does not significantly impact usage attitude from a technology acceptance perspective.

Table 7.
Direct and indirect effects results

Hypothesis (Path)	Direct effect	Indirect effect	Total effect
Performance expectancy -> emotional value	0.298**		0.298
Performance expectancy -> emotional value -> usage attitude		0.257**	0.257
Effort expectancy -> emotional value	0.009		0.009
Effort expectancy -> emotional value -> usage attitude		0.001	0.001
Facilitating conditions -> emotional value	0.163*		0.163
Facilitating conditions -> emotional value -> usage attitude		0.033*	0.033
Hedonic motivation -> emotional value	0.231**		0.231
Hedonic motivation -> emotional value -> usage attitude		0.156*	0.156
Emotional value -> usage attitude	0.443**		0.443
Performance expectancy -> functional value	0.401**		0.401
Performance expectancy -> functional -> usage attitude		0.175*	0.175
Effort expectancy -> functional value	-0.013		0.013
Effort expectancy -> functional value -> usage attitude		-0.012	0.012
Facilitating conditions -> functional value	0.211*		0.211
Facilitating conditions -> functional value -> usage attitude		0.018**	0.018
Hedonic motivation -> functional value	-0.029		0.029
Hedonic motivation -> functional value -> usage attitude		-0.006	0.006
Functional value -> usage attitude	0.352**		0.352

Note: * p<0.05, ** p<0.01.

5. Discussions

This study analyzed the relationship between the factors influencing generative AI service acceptance, based on UTAUT, and their effects on usage attitude through the mediating roles of emotional and functional value. The following key findings were derived: First, performance expectancy, facilitating conditions, and hedonic motivation significantly influenced emotional value, which in turn mediated their effects on usage attitude. This aligns with Bagozzi [64] and Venkatesh and Davis [22] who found that users exhibit positive emotional reactions when they believe a specific technology will enhance their work performance and when the supporting infrastructure for using the technology is well-established. Additionally, it was found that emotional reactions play a critical role in generative AI services.

These findings suggest that when users believe generative AI services can deliver the expected outcomes and when the necessary infrastructure and support are in place, they tend to develop more positive emotions toward the technology. In particular, hedonic motivation was found to play a significant role in shaping emotional value, confirming that the enjoyment and interest provided by generative AI services are crucial factors in technology acceptance. As noted by Brown and

Venkatesh [25], hedonic motivation plays a key role in shaping emotional value. The enjoyment experienced while using technology is an important factor in technology acceptance.

Unlike previous studies, this study emphasizes that in the context of a new technology such as generative AI, hedonic elements take on greater significance, particularly concerning the enjoyment provided through content generation and personalized services. This indicates that the enjoyment and satisfaction users derive from AI-generated content significantly contribute to shaping user attitudes. Generative AI services often build an "assistive" user environment centered around close interaction with individual users. Therefore, unlike other technologies, they are more heavily influenced by users' emotional value and relational dynamics. This underscores the importance of considering the dynamics of user experiences and enjoyment factors in the context of generative AI service usage.

Second, functional value, performance expectancy, and facilitating conditions were found to have positive effects and mediated their influence on usage attitude. This result aligns with Davis, et al. [13], Venkatesh and Davis [22], and Gefen, et al. [65], which demonstrated that when a technology is perceived to improve work efficiency, functional value increases, and both utility and supporting infrastructure play key roles in technology acceptance. Users highly value the functional value of generative AI services when they expect these services to help them perform tasks efficiently and deliver tangible outcomes. However, effort expectancy and hedonic motivation did not significantly affect functional value, marking a deviation from prior studies. This suggests that users' perceptions of the effort required to use a technology may not necessarily be a critical factor in increasing functional value. Particularly, as generative AI services are already designed to be easy to use, performance and supporting infrastructure appear to play a more significant role than ease of use. Unlike mobile or entertainment technologies, the enjoyment derived from generative AI services appears to strengthen emotional value rather than functional value. This indicates that the enjoyment users feel while using the service does not always translate into tangible, functional benefits.

Third, both emotional value and functional value positively influenced usage attitude, with emotional value having a stronger effect. This finding is consistent with Chitturi, et al. [37] and Van Der Heijden [41], reaffirming that positive emotional experiences provide stronger motivation for technology acceptance. When generative AI services provide users with positive emotional experiences, users are more likely to actively adopt and continuously use the technology [1]. These findings suggest that users develop a stronger emotional connection to the technology through emotional value factors such as creativity, enjoyment, and personalized experiences. The extent to which a technology provides enjoyment and satisfaction serves as a critical adoption factor. This study emphasizes that emotional value plays a more critical role than functional value in generative AI services. It highlights that emotional value is particularly significant in creative and engaging technologies such as generative AI, where the enjoyment and satisfaction users feel while using the technology are key factors in promoting technology acceptance.

Finally, effort expectancy was found to have no significant effect on either emotional value or functional value. This differs from Venkatesh and Davis [22], who argued that ease of use, or effort expectancy, positively influences technology acceptance intention, and Davis, et al. [13], who suggested that the easier a technology is perceived to be to use, the more positive users' attitudes and behavioral intentions become. In previous research, effort expectancy was considered a factor that reduces the mental and physical burden of learning and using technology, thereby increasing acceptance. However, the finding that effort expectancy did not significantly influence emotional or functional value in this study contradicts those results.

This suggests that ease of use may be relatively less critical for generative AI services compared to other technologies. New technologies such as generative AI provide greater enjoyment and creative possibilities compared to traditional technologies, offering users emotional satisfaction [3]. This explains why ease of use is no longer a primary evaluation factor, as advanced technologies already meet many user expectations. The diminishing impact of effort expectancy on technology acceptance aligns with certain findings from previous studies. This partially aligns with prior research, such as Poushneh and Vasquez-Parraga [42], which noted that as technology advances, ease of use may no longer be a primary determinant, as users may place less importance on the difficulty of using a technology. This confirms that rather than perceptions of effort, factors such as performance expectancy and supporting infrastructure, along with the value a service provides, play a more significant role in influencing usage attitudes.

In conclusion, this study emphasizes that both emotional and functional values are important for accepting generative AI services, but emotional value has a greater influence. For generative AI services, emotional experiences are a critical factor in technology acceptance. This highlights the unique characteristics of generative AI compared to traditional technologies and suggests that strategies aimed at enhancing emotional value can facilitate AI technology adoption. It also implies that strengthening user experience-focused strategies and development plans is essential for the successful implementation of AI services.

6. Conclusion

6.1. Research Implications

This study emphasized that performance expectancy, facilitating conditions, and hedonic motivation play critical roles in the acceptance of generative AI services, particularly confirming the importance of emotional value in enhancing user experience. Practical implications for expanding and strengthening user attitudes toward generative AI services were derived, focusing on three key points. These provide concrete strategies for creating an environment where users can more efficiently adopt and utilize generative AI services.

First, it is necessary to enhance functions and services that maximize performance expectancy. Maximizing the outcomes users expect from generative AI services is a crucial factor in fostering positive attitudes. To achieve this, features that provide tangible and personalized work efficiency must be strengthened. For example, automated content generation tailored to specific user needs, data analysis, and problem-solving functionalities should be provided to simplify routine tasks. Personalized recommendations or systems for automating creative tasks should help users experience clear outcomes through the service. When users perceive that they can achieve significant results through the service, a positive attitude will naturally form.

Second, infrastructure and support systems that strengthen facilitating conditions must be expanded. Building technological infrastructure and support systems to enable users to easily access and utilize generative AI services is essential. It is crucial to minimize the difficulties users face when using services by providing immediate technical support through customer service systems. Additionally, various educational materials, such as step-by-step guides, tutorials, and FAQs, should be provided to help users learn and utilize AI services more effectively. When such supporting infrastructure is well-established, users can reduce the burden of using the technology and form a positive attitude toward the service. Particularly when implementing AI services in corporate settings, the better the technical support and training systems are established at the organizational level, the more trust users will place in the service.

Third, enhancing user experiences that strengthen hedonic motivation is necessary. Generative AI services can positively reinforce usage attitudes through the enjoyment and interest users feel. Therefore, designing user experiences that maximize emotional satisfaction during service use is important. For example, providing features that allow users to perform creative tasks or generate entertaining content through generative AI can enhance hedonic motivation. This is particularly powerful in creative tasks such as content generation, where generative AI can provide users with positive emotional experiences. The more users have engaging and enjoyable experiences with generative AI, the more positive their attitudes toward the service will become, increasing the likelihood of long-term use.

Finally, to positively shift user attitudes toward generative AI services and expand their use, it is essential to strategically strengthen factors such as performance expectancy, facilitating conditions, and hedonic motivation. These strategies can not only help users understand the usefulness of AI but also encourage them to enjoy interacting with AI services, thereby fostering long-term use and loyalty. By delivering clear outcomes to users, strengthening technical support, and providing enjoyable user experiences, the successful adoption and widespread use of generative AI services will be promoted.

6.2. Research Limitations and Future Plans

This study holds significance as it verified the relationship between users' values and attitudes in the context of integrated technology acceptance for generative AI. However, this study has the following limitations: First, it was based on a cross-sectional survey conducted at a single point in time, limiting its ability to reflect changes in technology acceptance over time. Given the rapid evolution of generative AI technology, longitudinal research tracking changes in technology acceptance is necessary to analyze how user attitudes shift over time. In the future, instead of cross-sectional studies, research should be designed as longitudinal studies conducted every six months to explore the acceptance and usability of generative AI. Additionally, studies that incorporate various features and use scenarios of generative AI services should go beyond value and attitude to identify dynamic customer experiences, considering experiential factors. Second, this study was limited to generative AI users in South Korea. The use of generative AI varies across different social and cultural contexts, as well as by country and predominant services. Comparative studies analyzing users by country and region should be pursued. Furthermore, an in-depth exploration of the influence of social and cultural differences on generative AI service use is required.

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