

Article

Understanding Factors Influencing Generative AI Use Intention: A Bayesian Network-Based Probabilistic Structural Equation Model Approach

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Abstract: This study investigates the factors influencing users' intention to use generative AI by employing a Bayesian network-based probabilistic structural equation model approach. Recognizing the limitations of traditional models like the technology acceptance model and the unified theory of acceptance and use of technology, this research incorporates novel constructs such as perceived anthropomorphism and animacy to capture the unique human-like qualities of generative AI. Data were collected from 803 participants with prior experience of using generative AI applications. The analysis reveals that social influence (standardized total effect = 0.550) is the most significant predictor of use intention, followed by effort expectancy (0.480) and perceived usefulness (0.454). Perceived anthropomorphism (0.149) and animacy (0.145) also influence use intention, but with a lower relative impact. By utilizing a probabilistic structural equation model, this study overcomes the linear limitations of traditional acceptance models, allowing for the exploration of nonlinear relationships and conditional dependencies. These findings provide actionable insights for improving generative AI design, user engagement, and adoption strategies.

Keywords: generative AI; TAM; UTAUT; anthropomorphism; animacy; probabilistic structural equation model



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1. Introduction

The rapid advancements in artificial intelligence have catalyzed significant transformations across industries and societal domains [1]. Generative AI (GAI), a groundbreaking technology, has emerged as a distinct paradigm, contrasting with traditional AI's focus on structured data processing [2,3]. GAI models, trained on extensive datasets of natural language, images, and diverse media, demonstrate a remarkable ability to capture the nuances and patterns of human expression [3]. This enables them to generate original, contextually relevant outputs that resemble human-created content. From rational and creative text generation to the production of realistic images and sound data, generative AI shows a remarkable capacity to mimic and augment human-like capabilities. Applications like OpenAI's ChatGPT have showcased their proficiency in processing language and generating text outputs. This transformative potential has accelerated GAI's widespread adoption across sectors such as healthcare, finance, education, and software development [4–7]. GAI applications include assisting in drug discovery and diagnostics, enhancing data analysis and tailored services, supporting personalized learning experiences, and accelerating coding and debugging processes. Reflecting this promise, leading technology firms have committed substantial investments to advance GAI, with Microsoft alone investing approximately USD 13 billion in OpenAI. Industry forecasts suggest that the global AI market will

exceed USD 1.3 trillion by 2032, underscoring the economic significance of this field [8]. However, alongside its promising applications, GAI also introduces critical challenges. The capacity to generate deepfake content and realistic fake media has exacerbated concerns about misinformation, copyright disputes, and unethical uses. Additionally, questions surrounding intellectual property rights and the societal impact of AI's expanding role in traditionally human-dominated domains underscore the urgency for developing robust regulatory frameworks. This research seeks to expand the theoretical boundaries of existing models, such as the TAM and UTAUT, while offering practical insights for policymakers and industry leaders to promote the ethical and effective integration of GAI across diverse sectors, including healthcare, finance, education, and software development.

A key aspect of addressing these challenges lies in understanding how users perceive and accept GAI. Whether individuals find the technology useful, trustworthy, or easy to use directly impacts its adoption and integration. Theoretical frameworks, such as the technology acceptance model (TAM) by [9] and the unified theory of acceptance and use of technology by Venkatesh et al. [10], have been helpful in studying phenomena related to the adoption of information systems. The TAM emphasizes the importance of perceived usefulness and ease of use, while the UTAUT provides additional factors such as performance expectancy, social influence, and facilitating conditions [7]. However, these models have limitations; for instance, both rely heavily on the assumption of linear relationships between variables, which oversimplifies the complex, often nonlinear nature of human interaction with advanced technologies like GAI. Also, traditional methods like structural equation modeling (SEM) focus on fixed pathways, limiting their ability to discover emergent patterns within data or to capture contextual nuances [11]. These traditional methods could sometimes be less effective at addressing the uncertainties inherent in real-world scenarios, such as varying user motivations and external influences. Furthermore, GAI aspires to emulate human capabilities, including reasoning, natural interaction, and human-like intellectual creativity. Therefore, when studying user acceptance of GAI, it is imperative to explore the degree to which GAI exhibits humanization and animacy. These characteristics significantly influence how users perceive and engage with GAI, especially in environments where natural, human-like interactions are prioritized. However, traditional models like the TAM and UTAUT may have limitations in this context. These theoretical frameworks were developed during a period when information systems primarily facilitated unidirectional interactions between users and technology, without a focus on anthropomorphic or interactive elements. Consequently, TAM and UTAUT may fall short in comprehensively capturing the nuanced factors that influence user acceptance of GAI. To address this gap, it is essential to integrate constructs that account for GAI's anthropomorphism and animacy in the study of user acceptance, enabling a more accurate assessment of its adoption and interaction potential in human-centered applications.

In order to find a way to overcome these limitations, this study employs a probabilistic structural equation model (PSEM) based on Bayesian networks with an algorithm of equivalence (EQ) classes to explore factors affecting the adoption of generative AI from the perspective users. Unlike conventional methods, Bayesian networks allow for the modeling of conditional dependencies and nonlinear interactions among variables [12]. This approach enables a deeper exploration of complex relationships influencing user acceptance of GAI. By integrating PSEM into the study of generative AI's adoption, this research aims to expand the theoretical boundaries of the TAM and UTAUT while offering actionable insights for policymakers and industry leaders. Also, in order to reflect the aim of GAI's humanization, this research not only adopts the items in the TAM and UTAUT, but also employs factors to reflect the humanization of GAI, such as perceived anthropomorphism and perceived animacy suggested by Bartneck et al. [13] for studying robots and the theory of anthropomorphism by Epley et al. [14].

Such an approach not only enhances our understanding of user behavior but also supports the development of strategies to promote the ethical and effective integration of GAI across diverse sectors. This research will contribute to the ongoing discourse on the responsible and beneficial deployment of GAI, addressing critical challenges regarding AI's expanding role in traditionally human-dominated domains.

2. Related Works

2.1. *Anthropomorphism and Animacy*

The integration of anthropomorphism and animacy into the study of GAI adoption enriches the existing literature by addressing the nuanced, human-centric factors influencing technology acceptance. Prior studies could be cited to highlight the growing importance of anthropomorphism and animacy in the AI domain [13–19]. Anthropomorphism reflects the degree to which users perceive a system as having human-like qualities, such as intentions, emotions, or intelligence [13]. This perception significantly enhances user trust and engagement, particularly in technologies designed for social or interactive purposes [13,15–17]. For example, Yang, Liu, Lv, Ai, and Li [15] investigated the impact of anthropomorphic design in AI service agents on customer usage intentions and discovered that customers prefer more anthropomorphic agents when they feel a high sense of control. Also, Blut, Wang, Wunderlich, and Brock [17] examined how anthropomorphism in AI robots influences customer intentions. Their findings revealed that anthropomorphism enhances perceptions of intelligence and usefulness of AI robots, thereby increasing customer intentions to use service robots. Troshani, Rao Hill, Sherman, and Arthur [16] explored how the human-like attributes of AI applications, specifically anthropomorphism and intelligence, affect consumer trust and found that human-like features can enhance trust. In addition to anthropomorphism, animacy, which relates to the perception of a system as “alive” or intentional, is critical in fostering emotional connections and natural interactions [14,18,19]. For instance, Laban [19] investigated how perceptions of animacy in AI chatbots influence user engagement and suggested that users are more likely to engage with AI chatbots they perceive as having animacy. Also, Al-Qaysi, Al-Emran, Al-Sharafi, Yaseen, Mahmoud, and Ahmad [18] examined the influence of AI attributes including animacy on the use of generative AI and revealed that AI attributes, such as perceived anthropomorphism, animacy, and intelligence, had a positive influence on generative AI use. Therefore, by incorporating anthropomorphism and animacy, this research provides a comprehensive understanding of how human-like characteristics impact GAI adoption, offering actionable insights for developers seeking to design intuitive and engaging AI interfaces.

2.2. *Technology Adoption*

The TAM and UTAUT are widely used frameworks for understanding technology adoption, including GAI. The TAM focuses on two key factors: perceived usefulness, the belief that using a system enhances performance, and perceived ease of use, the belief that using the system requires minimal effort [9,20]. The UTAUT expands on the TAM by incorporating performance expectancy, effort expectancy, social influence, and facilitating conditions, alongside moderating factors like age and experience [10]. Recent studies have applied these models to explore GAI adoption. For instance, a TAM-based study on teachers' acceptance of GAI tools in classrooms found a strong positive correlation between perceived usefulness and acceptance, with perceived ease of use also playing a significant role [21]. Similarly, the UTAUT has been used to investigate GAI adoption in higher education, highlighting the influence of performance expectancy, effort expectancy, social influence, and facilitating conditions on behavioral intentions and usage [22]. Xin et al. [23] examined GAI adoption in EFL teaching in Indonesian higher education using the UTAUT

and found that performance expectancy and social influence positively influence adoption. Additionally, Yan and Yue [24] explored factors influencing GAI adoption in new product development teams using the UTAUT, and their key findings included performance expectancy as a top predictor of attitudes and task–tool fitness as the strongest predictor of behavioral intention. These findings underscore the relevance of the TAM and UTAUT frameworks in identifying key factors driving GAI adoption across various contexts. However, while these studies primarily relied on constructs from the TAM and the UTAUT to explore factors influencing GAI adoption, they often overlooked the ultimate objective of GAI: to emulate human-like behavior. This omission underlines a critical gap in the research, as the ability of GAI to act like a human could be a key determinant of its utility and acceptance across various contexts. Therefore, this research focuses not only on components of the TAM and UTAUT but also focuses on anthropomorphism and animacy to articulate the characteristics of GAI.

2.3. Generative AI Adoption

The adoption of GAI has garnered significant attention across various sectors, including education, service industry, software engineering, and healthcare [25–31]. Recent studies have identified several key factors influencing the acceptance and integration of GAI technologies. In the educational domain, research by Ivanov, Soliman, Tuomi, Alkathiri, and Al-Alawi [25] examined GAI adoption in higher education using the theory of planned behavior, and found that the perceived strengths of GAI positively influence attitudes, subjective norms, and perceived behavioral control, which in turn drive intentions and actual adoption. Within the service sector, a study by Gupta and Rathore [26] explored barriers, such as ethics, technology, cost, regulations, privacy, and digital infrastructure, to GAI adoption in service organizations through a mixed-method approach, and confirmed that these barriers are related to GAI adoption. This study identified that compatibility with existing workflows significantly influences adoption decisions, while factors such as perceived usefulness and social aspects were less impactful. Furthermore, an analysis by Russo [27] examined the complexities of integrating GAI into software engineering, and highlighted that individual, technological, and societal factors collectively affect adoption patterns, emphasizing the need for a comprehensive approach to understanding GAI integration. Jindal, Lungren, and Shah [28] explored how GAI can deliver value in health systems, emphasizing that users' willingness to adopt GAI ultimately depends on its perceived value, and concluded that maximizing this value requires cultural adaptation within health systems to align with the unique adoption patterns of generative AI. These former studies identically articulate the importance of exploring the factors affecting GAI adoption, and thus understanding factors influencing GAI adoption is crucial for developing strategies that facilitate effective implementation and address potential challenges.

As demonstrated in the previous studies mentioned above, GAI is being utilized across various fields based on its tremendous advantages. However, it is also true that concerns exist regarding potential harm caused by its misuse. To address the safety concerns surrounding the adoption of GAI, it is crucial to consider its potential for malicious exploitation by adversaries. For instance, GAI can be leveraged to launch attacks, such as identity spoofing or unauthorized access, posing significant risks. Recent studies, such as F2Key, which dynamically convert facial features into private keys using COTS headphones [32], and AFace, a range-flexible anti-spoofing face authentication method using smartphone acoustic sensing (UbiComp'24), provide valuable insights into both the threats and defenses related to GAI applications. These examples highlight the importance of developing robust safeguards to mitigate privacy and security vulnerabilities in GAI usage [33]. Therefore, when adopting generative AI, it is important to consider not only its advantages but also the potential risks mentioned above.

3. Materials and Methods

3.1. Research Data

This research used an online survey platform, Prolific [34], to gather a cohort of 815 participants who had prior experience of using GAI, such as ChatGPT, Claude, and Gemini, between 18 October and 1 November 2024. Participants were selected based on specific pre-screening criteria to ensure relevance to the study. These criteria included prior usage experience with at least one generative AI tool within the last six months and fluency in English, which was ensured by restricting recruitment to participants from the United States, the United Kingdom, and Ireland. While efforts were made to achieve demographic diversity in terms of age, gender, and geographic location, the Prolific screening policy limited extensive customization, as adding more detailed filters significantly increased costs. As a result, the final sample reflected a balance between diversity and feasibility within the constraints of the platform. Prior to the survey, all participants were thoroughly informed about the survey and provided with comprehensive explanations of the survey procedures and objectives. After obtaining informed consent, participants were instructed to fill out the questionnaire (see Table 1). To enhance data reliability, the questionnaire incorporated five attention-check questions evaluating participants' comprehension of the questionnaire. Responses that failed to accurately address the attention-check questions were flagged for removal. Additional data cleansing steps included identifying and excluding responses with completion times under 2 min (indicating insufficient attention) or exceeding the 60 min time limit, which could signal distraction or disengagement. Responses with missing data for any item and/or clear patterns of repetition were also excluded. After applying these criteria, data from 803 participants was retained for further investigation. The data showed that 41.8% of participants were female, and 58.2% were male. Most were in their 20s (35.0%) and 30s (39.1%), with smaller proportions in their 40s (17.1%) and 50s or older (8.8%). Regarding education, the majority held an undergraduate degree (52.2%), followed by postgraduate (19.1%), college (16.7%), and high school (12.1%) levels. In terms of frequently used GAI applications, ChatGPT dominated, with 70.5% usage, followed by Claude (13.8%), Gemini (9.1%), and others (6.6%). Table 2 shows the demographic information of the final data sample.

All participants received GBP 2 for their contribution. The session had an average duration of approximately 15 min. The questionnaire used a seven-point Likert scale, ranging from strongly disagree (1) to strongly agree (7), to assess the participants' responses. The reason why this research chose the Likert scale for questionnaire responses is because it provides a simple, standardized, and effective way to measure attitudes, perceptions, and opinions [36,37]. Its ordinal nature allows respondents to express varying levels of agreement or disagreement, which enhances the granularity of data collection compared to binary scales [38]. Additionally, the Likert scale is widely recognized in research, making it easier to compare and interpret results while maintaining consistency with existing studies [37].

Table 1. Questionnaire used in this research.

Construct	Item	Mean	SD	Questionnaire	Reference
Intention to use	ITU1	4.29	1.47	I intend to use this generative AI application in the future	Davis [9]
	ITU2	4.59	1.32	I will frequently use this generative AI application for my tasks	
	ITU3	4.22	1.39	Given the opportunity, I would like to use this generative AI application	
	ITU4	4.59	1.26	I am likely to rely on this generative AI application whenever possible	

Table 1. Cont.

Construct	Item	Mean	SD	Questionnaire	Reference
Perceived Anthropomorphism	PA1	3.96	1.37	This generative AI application behaves as if it has their own intentions	Bartneck, Kulić, Croft and Zoghbi [13], Epley, Waytz and Cacioppo [14]
	PA2	5.37	1.15	I perceive this generative AI application as having human-like characteristics	
	PA3	5.09	1.21	This generative AI application seem to express emotions similar to humans	
Perceived Animacy	PN1	4.12	1.39	This generative AI application appears to be alive	
	PN2	3.58	1.27	The movements of this generative AI application seem natural, as if it were a living being	
	PN3	3.37	1.57	This generative AI application gives the impression that it has a life of its own	
	PN4	3.37	1.58	The behavior of this generative AI application feels intentional, as if it has its own will	
Perceived Usefulness	PU1	5.05	1.05	Using this generative AI application enhances my performance in tasks	Davis [9]
	PU2	4.67	1.12	This generative AI application is useful for accomplishing my goals	
Perceived Ease of Use	PEOU1	5.4	1.13	Learning to operate this generative AI application is easy for me	
	PEOU2	3.03	1.59	I find this generative AI application easy to use	
	PEOU3	5.52	0.99	It is easy to get the generative AI application to do what I want it to do	
	PEOU4	5.37	1.14	My interaction with this generative AI application is clear and understandable	
Performance Expectancy	PE1	3.58	1.36	I expect this generative AI application to improve my productivity	Venkatesh, Morris, Davis and Davis [10], Venkatesh and Bala [35]
	PE2	3.76	1.31	This generative AI application helps me accomplish tasks more efficiently	
	PE3	3.73	1.4	Using this generative AI application enhances the quality of my work	
	PE4	3.45	1.47	I believe this generative AI application will be beneficial for my performance	
Effort Expectancy	EE1	5.22	1.12	I feel confident in my ability to use this generative AI application without much assistance	
	EE2	5.23	1.11	The steps to complete tasks using this generative AI application are straightforward	
	EE3	5.33	1.02	This generative AI application requires minimal effort to learn and use effectively	
	EE4	4.93	1.09	I believe that using this generative AI application will not require much time to become proficient	
	EE5	5.35	0.88	Navigating through this generative AI application feels intuitive and hassle-free	
Social Influence	SI1	5.15	1.03	People whose opinions I value recommend that I use this generative AI application	
	SI2	4.7	1.25	People who are important to me think I should use this generative AI application	
	SI3	5.11	0.98	The use of this generative AI application is supported by my organization or social group	
	SI4	5.03	1.16	I feel pressure from others to use this generative AI application	

Table 2. Demographic information of the data sample.

Variable		N	%
Gender	Female	336	41.8%
	Male	467	58.2%
Age group	20s	281	35.0%
	30s	314	39.1%
	40s	137	17.1%
	50s or older	71	8.8%
Final education	High school	97	12.1%
	College	134	16.7%
	Undergraduate	419	52.2%
	Postgraduate	153	19.1%
Frequently Used GAI	ChatGPT	566	70.5%
	Claude	111	13.8%
	Gemini	73	9.1%
	Others	53	6.6%

3.2. Data Analysis

The dataset was analyzed using a Bayesian network-based PSEM approach, leveraging an unsupervised EQ algorithm, which could enhance the depth and breadth of the analysis [39]. Bayesian modeling has been widely used in studies to predict the intentions of individuals [39–41]. For example, Khalid and Anwar [40] used Bayesian model averaging to analyze the relationship between environmental factors and EV adoption, and revealed a weak overall effect of environmental concerns on EV adoption, with significant variations by EV type and regional infrastructure. Kim, Lee, and Lee [39] utilized Bayesian-based PSEM to analyze users' intention to recommend an airport, and discovered that fundamental factors, such as queuing time, Wi-Fi connectivity, and airport staff, are the most crucial factors influencing users' intention. Also, Idan [41] analyzed the inference of social network users' behavioral intentions, using a Bayesian network to capture the dynamic decision-making processes of users in relation to privacy risks. The EQ algorithm offers distinct advantages over alternative Bayesian network methods such as Naïve Bayes, TAN, Hill-Climbing, K2, and Sparse Candidate, particularly in its ability to handle complex, real-world data relationships [42–45]. Unlike Naïve Bayes and TAN, which rely on simplifying assumptions like variable independence or tree-like structures, EQ enables the modeling of more nuanced relationships by grouping potential network structures into equivalence classes [44,45]. This approach allows the algorithm to explore the search space efficiently without being constrained by restrictive assumptions, making it better suited for high-dimensional data [43]. Furthermore, the EQ algorithm excels at capturing non-linear relationships and conditional dependencies, critical for understanding multifaceted phenomena like generative AI adoption [45]. Methods like Hill-Climbing and K2 often struggle with these complexities due to their reliance on stepwise optimization or predefined variable orders, which can lead to incomplete or biased models [46–48]. In contrast, EQ dynamically adapts to the data, identifying latent patterns and hidden dependencies that other algorithms might miss, and because of this flexibility, the EQ algorithm can ensure the robust handling of noise and uncertainty, which are common issues in user behavior datasets [44,45].

Compared to traditional structural equation modeling, the PSEM approach based on Bayesian networks offers the advantage of computing posterior probabilities for all network nodes in an omnidirectional manner, without being constrained by the directionality of the connections [49]. Conventional structural equation modeling blends statistical data and qualitative causal assumptions to uncover causal relationships. However, this methodology

frequently treats these relationships as deterministic, assuming that they exhibit precise cause-and-effect connections [50]. In contrast to traditional approaches, PSEM embraces the probabilistic nature of relationships, acknowledging the inherent uncertainties in causal connections [51]. This probabilistic perspective offers distinct advantages, as PSEM can be preferred over SEM due to its efficiency in model generation. By leveraging machine learning algorithms, PSEM can automatically and swiftly generate models, thereby streamlining the time-consuming steps often associated with other methods [39]. Moreover, in contrast to traditional SEM, PSEM sets itself apart by utilizing a Bayesian network structure, rather than solely relying on a series of linear equations [51]. This probabilistic approach offers distinct advantages, as it can more effectively model the complex, often nonlinear relationships inherent in human–technology interactions [51]. Table 3 presents a brief comparison between traditional approaches and PSEM.

Table 3. PSEM vs. other approaches.

Methodology	Key Characteristics	Strengths	Limitations	Advantages of PSEM
SEM	Analyzes latent variable relationships; assumes linearity	Good for latent constructs and clear models	Limited to linear relationships; less flexible	More flexible and captures uncertainty; captures nonlinear and causal relationships; more interpretable and models probabilistic relationships
Regression Analysis	Models linear relationships between variables	Simple, interpretable, and efficient	Cannot handle nonlinear or complex dependencies	
Decision Tree	Splits data into simple, interpretable rules	Intuitive and works with small datasets	Prone to overfitting; no probabilistic modeling	

This study utilized PSEM with BayesiaLab 11 software [52] to capitalize on its efficient algorithm for automatic model generation and its robust capabilities for conducting in-depth model analysis [53].

PSEM demonstrates three key features that distinguish it from traditional structural equation modeling approaches [39]. PSEM’s inherent probabilistic nature enables the modeling of complex interdependencies among variables, proving instrumental in managing uncertainties found in real-world data [51]. Additionally, PSEM’s nonparametric quality allows it to accommodate and elegantly represent nonlinear relationships between categorical variables, a crucial capability when dealing with multifaceted datasets. Furthermore, PSEM’s dynamic structure is molded and informed by the data themselves, rather than solely relying on theoretical assumptions, ensuring the development of a grounded and adaptable model that accurately reflects the underlying patterns and relationships [39,51,54]. The incorporation of PSEM was influential in uncovering insights that are both intricate and firmly rooted in the dataset, thereby enhancing the robustness of the findings [54].

4. Results

Before conducting comprehensive PSEM analysis, this study compared the performance of the EQ algorithm to other common machine learning techniques, including logistic regression, decision tree, support vector machine, neural network, random forest, adaboost, and bagging. Below is a brief explanation of each technique and a comparison to the EQ algorithm:

Logistic regression is a widely used statistical method for binary classification, modeling the probability of a categorical outcome based on independent variables [55,56]. While it is simple, efficient, and interpretable, it assumes a linear relationship between features and the log-odds of the outcome, which limits its ability to capture nonlinear relation-

ships [55,56]. In contrast, the EQ algorithm can effectively model complex dependencies and conditional relationships, which logistic regression cannot address [42].

Decision trees split data hierarchically based on feature values, making them intuitive and capable of handling categorical and continuous variables [57,58]. However, they are prone to overfitting, especially with noisy or high-dimensional data, reducing generalizability [57,58]. The EQ algorithm overcomes these issues by focusing on probabilistic relationships and capturing the dependencies between variables through Bayesian network structures, providing a more robust and interpretable model [42].

SVMs classify data by finding the hyperplane that best separates classes in a high-dimensional space, making them effective for datasets with clear margins, but they are computationally expensive for large datasets and lack interpretability [59,60]. The EQ algorithm, in contrast, offers an interpretable probabilistic framework that models uncertainty and causal relationships, which SVMs cannot provide [42].

Neural networks are highly flexible and excel at learning complex, nonlinear patterns in data, but they require significant computational resources, are prone to overfitting, and often lack interpretability [61,62]. The EQ algorithm, while less flexible in general-purpose applications, is computationally efficient in discovering Bayesian network structures and provides interpretable results by capturing conditional independencies in data [42].

Random forests combine multiple decision trees to improve classification accuracy and reduce overfitting, making them robust for high-dimensional data, but they do not inherently model probabilistic relationships and can lack interpretability [63,64]. The EQ algorithm provides deeper insights by capturing probabilistic and causal relationships among variables, making it more suitable for applications requiring an understanding of the data structure [42].

AdaBoost is an ensemble method that iteratively combines weak classifiers, typically decision trees, to create a strong classifier by focusing on misclassified samples [65,66]. While it effectively reduces bias, it is sensitive to noisy data and lacks the capacity to model probabilistic relationships [65,66]. The EQ algorithm, on the other hand, is designed to discover and represent the probabilistic structure in data, providing an advantage in tasks requiring uncertainty modeling [42].

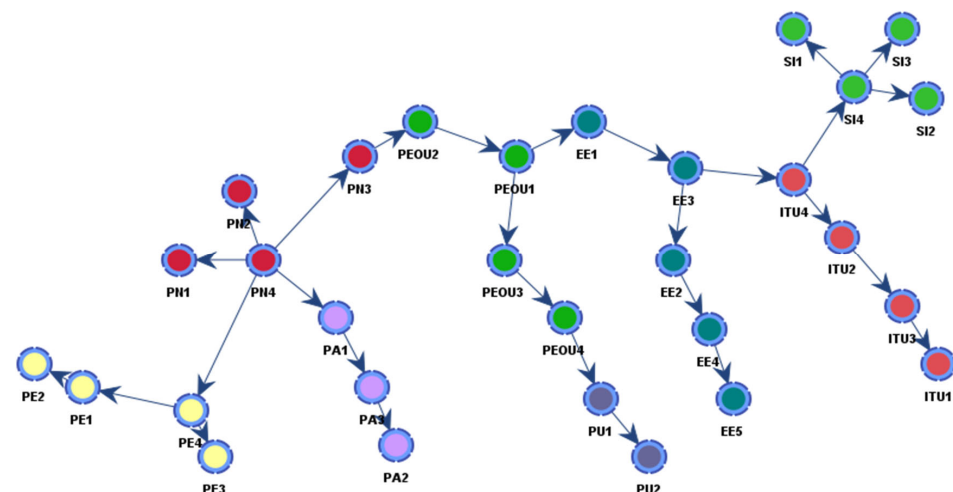
Bagging reduces variance by training multiple models on bootstrapped datasets and averaging their outputs, making it effective for reducing overfitting, but like other ensemble methods, it does not provide insights into probabilistic dependencies or causal relationships between variables [67,68]. The EQ algorithm excels in these areas, making it a more interpretable and theoretically grounded choice for Bayesian network structure learning [42].

The accuracy, recall, and precision metrics in Table 3 were derived using a 10-fold cross-validation approach. For performance measurement, the mean of three values from the 'intention to use' construct was set as the target variable. The responses in this study were encoded as continuous variables using a seven-point Likert scale. This approach allows the retention of the full variability in participants' responses, ensuring that subtle differences in perceptions are captured effectively. Encoding the responses as continuous variables is consistent with the PSEM approach employed in this study, as it enables the exploration of nuanced relationships and nonlinear dependencies between constructs. This comparison was performed to verify whether the EQ algorithm could provide reasonable performance. As presented in Table 4, the EQ algorithm's performance was found to be superior to the other benchmarking algorithms, with measurement scores higher than 90%. Additionally, considering the significant advantage of the straightforward interpretations provided by the graphical representation of the Bayesian network [51], this research concluded that the Bayesian EQ algorithm can be used as the research analysis methodology.

Table 4. The results of the performance test: EQ vs. common benchmark models.

Model	Accuracy	Precision	Recall	ROC
Equivalence Classes (EQ)	0.944	0.942	0.942	0.977
Logistic Regression	0.834	0.857	0.816	0.939
Decision Tree	0.751	0.741	0.800	0.749
Random Forest	0.826	0.849	0.808	0.923
Support Vector Machine	0.838	0.847	0.840	0.934
Neural Network	0.826	0.855	0.800	0.901
AdaBoost	0.805	0.815	0.808	0.910
Bagging	0.817	0.858	0.776	0.897

Then, variable clustering was conducted. The variable clustering process in BayesiaLab uses a hierarchical agglomerative clustering algorithm, starting with each manifest variable as a separate cluster and merging them iteratively based on arc force, derived from Kullback–Leibler divergence, to group statistically dependent variables [51,69]. Criteria such as the stop threshold and maximum cluster size guide the merging process [51]. Then, clusters are validated with 10-fold cross-validation to ensure structural reliability, and latent variables are created to represent hidden common causes [51]. Finally, results are visualized in a hierarchical Bayesian network that integrates manifest and latent variables for probabilistic modeling [51]. As a result, a total of eight groups were created, as shown in Figure 1: intention to use, perceived anthropomorphism (PA), perceived animacy (PN), perceived usefulness (PU), perceived ease of use (PEOU), performance expectancy (PE), effort expectancy (EE), and social influence (SI). The network illustrates how items are grouped under their respective constructs, showing clear clusters in the circles (i.e., nodes) with the same colors, such as performance expectancy (PE1–PE4), perceived animacy (PN1–PN4), perceived animacy (PA1–PA3), perceived ease of use (PEOU1–PEOU4), effort expectancy (EE1–EE5), intention to use (ITU1–ITU4), and social influence (SI1–SI4), where variables within the same construct are strongly connected, indicating high internal consistency. Constructs such as perceived animacy and perceived anthropomorphism exhibit strong mutual connections, reflecting their combined influence on user perceptions. Similarly, perceived ease of use and perceived usefulness are closely linked, emphasizing their interdependence in shaping the ease and utility perceptions of the system. Furthermore, social influence and effort expectancy demonstrate a significant direct link to intention to use, highlighting their critical role in driving adoption behavior. This clustering and interconnectivity across constructs reveal the structured relationships between variables, with distinct internal groupings and conditional dependencies between related constructs.

**Figure 1.** Variable clustering for building PSEM.

Next, multiple clustering was first conducted to create new constructs based on the variable clustering, and then unsupervised learning with the EQ algorithm was performed to formulate the final PSEM, according to the guidelines of Conrady and Jouffe [51]. Figure 2 presents the final PSEM, and Table 5 shows that all children nodes have mutual information with the target node ‘intention to use’. It was identified that the three most influential nodes affecting the target node were ‘social influence’, ‘effort expectancy’, and ‘perceived usefulness’, with mutual information over 10%.

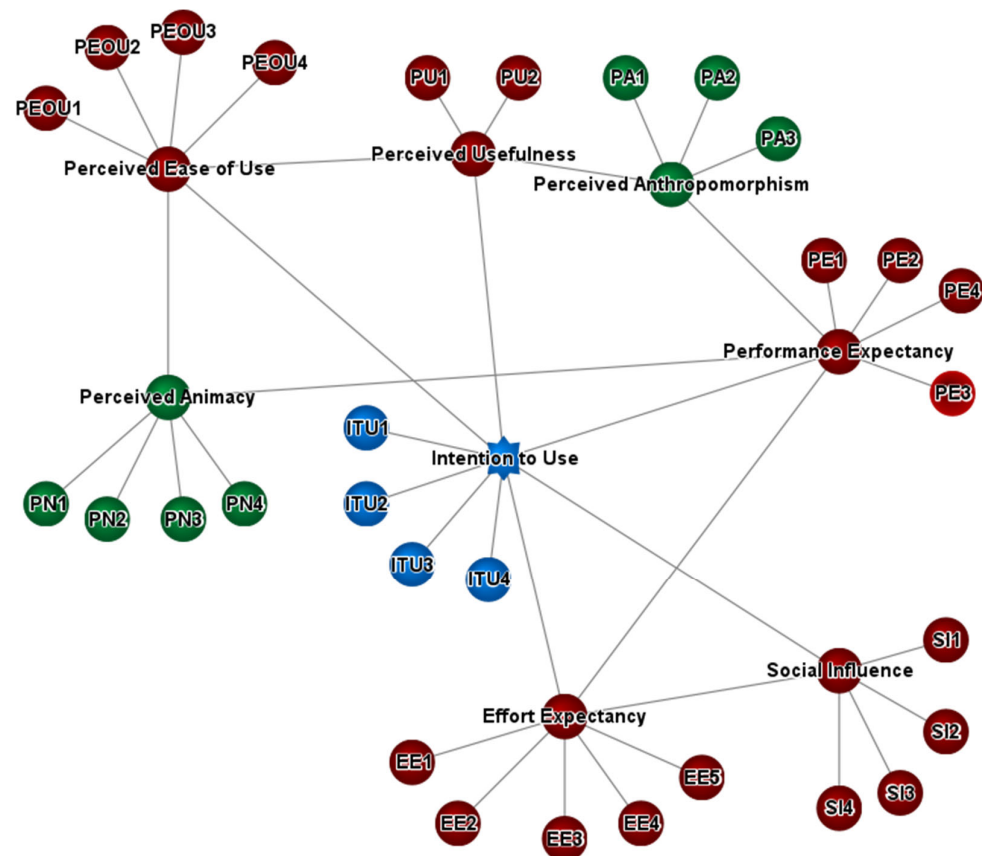


Figure 2. PSEM based on the EQ-Bayesian network (target node: intention to use).

Table 5. Descriptive statistics from the EQ network (target node: intention to use).

Node	Relative Binary Mutual Information	Posterior Mean	Max Bayes Factor	Min Bayes Factor
Social Influence	17.56%	4.56	3.93	−5.39
Effort Expectancy	12.88%	4.86	4.02	−2.93
Perceived Usefulness	12.58%	4.52	4.19	−4.19
Perceived Ease of Use	6.62%	4.70	3.11	−3.11
Performance Expectancy	8.33%	3.42	2.40	−5.60
Perceived Anthropomorphism	1.27%	4.87	1.34	−1.34
Perceived Animacy	1.24%	3.36	1.46	−1.46

The analysis revealed that all offspring nodes exhibited significant relationships with the target node ‘intention to use’ in terms of standardized total effect. In the context of PSEM, standardized total effects are crucial to consider, as they encompass the combined direct and indirect influences that one variable exerts on another within the model [39]. Standardized total effects provide a comprehensive measure of the strength and significance of these relationships, enabling researchers to fully understand the impact of predictors on outcomes, including the mediating effects of other variables [51]. This understanding is essential for accurate interpretation and informed decision-making based on the model’s

findings [39]. As shown in Table 6, the results for the standardized total effect straightforwardly emphasize the significance of the nodes to the target node (i.e., intention to use). Social influence is the most important node affecting the target node, with a standardized total effect score of 0.550. Effort expectancy (standardized total effect = 0.480) and perceived usefulness (standardized total effect = 0.454) were also crucial factors after social influence. Performance expectancy, perceived anthropomorphism, and perceived animacy had significant effects on the target node, but their effects were relatively weaker compared with the other offspring nodes.

Table 6. The results of PSEM to the target node (i.e., intention to use).

Node	Mean	Standardized Total Effect	G-Test	df	p-Value
Social Influence	5.005	0.550	323.145	4.000	0.000
Effort Expectancy	5.222	0.480	285.323	4.000	0.000
Perceived Usefulness	4.873	0.454	182.812	2.000	0.000
Perceived Ease of Use	4.811	0.395	162.177	2.000	0.000
Performance Expectancy	3.619	0.190	110.525	4.000	0.000
Perceived Anthropomorphism	4.985	0.149	18.333	2.000	0.000
Perceived Animacy	3.516	0.145	16.993	2.000	0.000

5. Discussion

This study aimed to analyze the key factors that influence the adoption and usage of generative AI technologies by employing a Bayesian network-based probabilistic structural equation modeling approach. This study sought to address the limitations of the technology acceptance model and the unified theory of acceptance and use of technology by taking a more comprehensive and quantitative approach. Specifically, it systematically evaluated the relative contribution and interplay of various variables, such as perceived anthropomorphism, effort expectancy, perceived usefulness, and social influence, using standardized total effect values. This allowed the researchers to gain a deeper and more nuanced understanding of the complex dynamics that drive the adoption and acceptance of GAI technologies among users.

Social influence emerged as the most significant predictor, with a standardized total effect value of 0.550. This indicates that social contexts and opinions from peers, friends, or experts are critical factors in users' decisions to adopt GAI. Positive feedback from social networks has a direct impact on user behavior, making social influence one of the most important drivers of GAI adoption. Notably, the effects of social influence go beyond the direct utility of the technology, fulfilling users' needs for belonging and social recognition. These findings highlight the necessity of socially driven campaigns and educational programs to promote GAI adoption. Furthermore, fostering user interaction and creating collaborative environments within organizations can strengthen the positive evaluation of GAI and enhance users' intention to adopt the technology. Effort expectancy and perceived usefulness were also found to be key factors. Effort expectancy, with a standardized total effect value of 0.480, revealed that users' perceptions of how easily they can learn and use GAI significantly influence adoption. Similarly, perceived ease of use, with a standardized total effect value of 0.395, underscores the importance of intuitive user interfaces and straightforward learning experiences, particularly for non-technical users. These results suggest the need for simplified design and robust educational materials to facilitate technology adoption. Perceived usefulness, with a standardized total effect value of 0.454, demonstrated that users' belief in GAI's ability to improve personal or professional outcomes strongly drives adoption. This underscores the importance of marketing messages that emphasize the tangible benefits of GAI while clearly presenting its outcomes, thereby fostering trust and increasing user confidence. Perceived anthropomorphism and perceived animacy had stan-

standardized total effect values of 0.149 and 0.145, respectively. While these factors positively influenced adoption, their effects were relatively weaker compared to other variables. These findings suggest that while users appreciate human-like characteristics in GAI, practical functionality and efficiency have a greater impact on adoption. The results highlight the need for design improvements that enhance emotional connections between users and GAI, such as incorporating emotion recognition and non-verbal communication features. Future research should explore ways to further strengthen perceived anthropomorphism and animacy to improve user experience and foster emotional engagement. Performance expectancy, with a standardized total effect value of 0.190, had a comparatively lower influence on GAI adoption. The relatively lower influence of performance expectancy on GAI adoption can be attributed to several factors. First, as GAI is still an emerging technology, users may lack confidence in its performance and reliability, particularly if the outputs are inconsistent or prone to errors. Second, many users may not fully comprehend how GAI can directly contribute to their personal or professional success, as concrete use cases and tangible benefits are not yet widely demonstrated. Additionally, the cognitive burden of effectively learning to use GAI may deter users, leading them to perceive the effort as outweighing the potential performance benefits. Furthermore, GAI's instrumental role often lacks psychological satisfaction or emotional connection, making performance less influential compared to social influence and effort expectancy. Finally, as a multipurpose tool, GAI may not be optimized for specific tasks, leaving users uncertain about its effectiveness in meeting their unique needs. Addressing these issues through the clear communication of use cases, enhancing reliability, and emphasizing emotional engagement alongside technical performance could help to improve the role of performance expectancy in GAI adoption.

The lower impact of performance expectancy compared to social influence, effort expectancy, and perceived usefulness can be explained by the unique characteristics of generative AI systems and their adoption context. Performance expectancy, which reflects users' beliefs about the system's ability to deliver efficient and effective outcomes, may hold less immediate importance when generative AI is perceived as an innovative or experimental technology still in its early adoption phase. In such cases, users are more likely to rely on social influence, as recommendations and endorsements from peers or influencers provide trust and confidence in engaging with unfamiliar technologies. Effort expectancy also plays a significant role, as the ease of learning and interacting with generative AI tools often becomes a primary concern, especially for users who are new to such systems. Perceived usefulness, by contrast, directly addresses the immediate value and practical benefits that users associate with the technology, making it a stronger driver of behavioral intention. Performance expectancy, while conceptually related to usefulness, is often seen as a long-term evaluation of the system's outcomes and therefore may carry less weight in the initial decision-making process. This distinction helps to clarify why performance expectancy had a lower relative impact compared to other constructs in the context of generative AI adoption.

This study makes a significant contribution to the field of technology acceptance research by addressing the limitations of the widely used technology acceptance model and the unified theory of acceptance and use of technology. It introduces a novel methodological approach that overcomes the shortcomings of these existing theories. The TAM primarily focuses on perceived usefulness and ease of use, but it does not adequately explain the nonlinear relationships between variables, particularly in the context of complex technological systems. Similarly, while the UTAUT expands upon the TAM by incorporating social influence and facilitating conditions, it lacks the ability to quantitatively evaluate the interaction effects between variables or account for emerging factors such as anthropomorphism

and animacy. To address these limitations, this study employs a Bayesian network-based probabilistic structural equation modeling approach. This methodological advancement allows the researchers to analyze nonlinear interactions and assess the moderating effects of social influence on the relationship between effort expectancy and perceived usefulness. Furthermore, this study integrates new variables, such as perceived anthropomorphism and animacy, to provide valuable insights into the emotional dynamics of user-technology interactions. This novel methodological approach addresses the quantitative limitations of existing theories and introduces a fresh perspective on technology acceptance research, paving the way for a more comprehensive understanding of the complex factors that drive the adoption and use of emerging technologies, such as generative AI.

The findings of this study have several practical implications. To promote GAI adoption, it is essential to strengthen social foundations through strategies such as peer learning and community-based programs that enable users to experience the benefits of GAI. During the early stages of implementation, emphasizing collaboration and feedback among users can streamline the adoption process. Additionally, designing user-friendly interfaces and providing comprehensive support materials can help to include non-expert users. Strengthening human-like features, such as voice recognition, emotional expression, and non-verbal interactions, can enhance emotional connections and build trust among users. Such design improvements not only increase adoption rates but also ensure long-term user satisfaction. Furthermore, organizations can incentivize GAI adoption by integrating it into performance metrics, reward systems, and professional development programs. This can foster a culture of innovation and encourage employees to explore and embrace the benefits of technology. Additionally, developing comprehensive training programs that address both technical and user-centric aspects of GAI can empower individuals to leverage technology effectively. These training programs should cover topics such as responsible use, ethical considerations, and practical applications, ensuring that users are equipped with the necessary knowledge and skills to maximize the benefits of GAI while navigating its complexities.

One limitation of this study is its reliance on a single dataset obtained through the Prolific online survey platform, which introduces the potential for sampling bias. While efforts were made to ensure participant diversity, the sample may not fully represent the broader population of generative AI users, particularly across different cultural or professional contexts. Additionally, this study primarily focuses on a single demographic, limiting the generalizability of the findings to more diverse user groups. To address these limitations, future research should incorporate datasets from multiple sources to reduce sampling bias and ensure greater representativeness. Conducting cross-cultural studies will be particularly valuable for exploring how cultural and regional differences influence generative AI adoption. Expanding the demographic and professional diversity of participants will also provide a more comprehensive understanding of the factors driving adoption and use across varied contexts. By addressing these gaps, future studies can enhance the applicability and robustness of insights into generative AI adoption. This study's reliance on cross-sectional data restricts its ability to analyze changes in technology adoption over time, limiting the findings to factors influencing adoption at a specific point. To address this limitation, future research should employ longitudinal approaches to investigate the evolving dynamics of GAI adoption over an extended period. This would provide deeper insights into how user perceptions, behaviors, and adoption patterns shift as the technology matures and becomes more widely used. Expanding the research scope to include longitudinal data would enable valuable insights into the long-term evolution of GAI adoption and its implications for technology development, marketing, and policy decisions. Such longitudinal investigations could shed light on how adoption patterns

and the relative importance of various factors may change over time and across different contexts, providing a more nuanced and holistic understanding of the complex dynamics involved in the widespread acceptance and use of generative AI technologies.

6. Conclusions

This study offers a comprehensive examination of the multifaceted factors influencing the adoption of generative AI. The findings reveal that social influence, effort expectancy, and perceived usefulness are pivotal drivers of GAI adoption, underscoring the importance of user-centric design and socially embedded promotion strategies. Additionally, constructs such as perceived anthropomorphism and animacy, while less influential, suggest avenues for enhancing user engagement through emotionally resonant and human-like interactions. This research advances the methodological landscape by employing Bayesian network-based probabilistic structural equation modeling, which enables the capture of complex, nonlinear relationships among variables. This innovative approach provides a richer and more nuanced understanding of the interplay between user perceptions and adoption intentions, addressing limitations in the traditional technology acceptance model and unified theory of acceptance and use of technology frameworks. In conclusion, this study offers actionable insights for practitioners and policymakers seeking to foster the ethical and effective integration of GAI. By addressing identified gaps and leveraging the proposed strategies, organizations can enhance user acceptance, optimize technological design, and unlock the transformative potential of GAI in diverse domains, including healthcare, education, and creative industries.

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Abbreviations

The following abbreviations are used in this manuscript:

EE	Effort expectancy
EQ	Equivalence classes
GAI	Generative artificial intelligence
ITU	Intention to use
PA	Perceived anthropomorphism
PE	Performance expectancy
PEOU	Perceived ease of use
PN	Perceived animacy
PSEM	Probabilistic structural equation model
PU	Perceived usefulness
ROC	Receiver operating characteristic
SEM	Structural equation modeling
SI	Social influence
TAM	Technology acceptance model
UTAUT	Unified theory of acceptance and use of technology

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