

FROM ENJOYMENT TO UTILITY: DETERMINANTS OF DIGITAL NATIVES' ADOPTION OF GENERATIVE ARTIFICIAL INTELLIGENCE

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Abstract

GenAI's growing popularity has altered the way digital natives approach their work and schoolwork. Since most people choose not to utilize GenAI, it is crucial to determine what makes people want to perform certain things. This study uses the Unified Theory of Acceptance and Use of Technology (UTAUT2) to investigate the elements that impact the intents of digital natives to use generative AI. Our quantitative cross-sectional research included 152 digital natives residing in Jakarta who had prior experience working with generative AI technologies. In order to analyze the collected data, Partial Least Squares-Structural Equation Modeling (PLS-SEM) was used. The results show that effort and performance anticipation have a favorable effect on behavioral intention, which shows how important it is to have high hopes for performance improvements and simplicity of use to encourage adoption. Social influence has a statistically meaningful, although minor, effect on behavioral intention, in contrast to hedonic incentive, which does not. Overall, the model demonstrates moderate explanatory power, suggesting that generative AI adoption among digital natives is primarily driven by utilitarian considerations. These findings imply that generative artificial intelligence is mainly perceived as a functional, productivity-oriented tool rather than a source of enjoyment. The study offers practical implications for institutions and developers to prioritize usability and performance value when encouraging GenAI adoption in academic and professional context.

1. INTRODUCTION

The rapid development of generative artificial intelligence (GenAI) has increasingly transformed the way individuals perform academic and professional tasks. Unlike earlier digital technologies that primarily supported information retrieval or routine automation, generative AI systems—such as large language models—are now actively involved in content generation, analytical reasoning, and decision-support activities. As a result, GenAI is no longer perceived merely as a technological novelty, but as a practical tool that is embedded in everyday task execution and problem-solving processes, particularly among digital natives (Feuerriegel and Janiesch 2024).

One defining characteristic of generative AI adoption is its predominantly voluntary nature. In most academic and workplace settings, the use of GenAI tools is not formally mandated by institutions or organizations. Instead, individuals independently decide whether to adopt and continue using these technologies based on their own experiences and evaluations. Consequently, users' behavioral intention becomes a critical factor in explaining continued adoption, as it reflects personal judgments regarding usefulness, ease of use, and relevance to task demands (Gazit et al. 2025). Understanding the determinants of this intention is therefore essential for explaining why some users actively integrate generative AI into their activities while others do not.

Previous studies on voluntary technology adoption have widely employed intention-based acceptance models to explain user behavior. Among these models, UTAUT2 has seen extensive use due to its ability to include both

practical and intrinsic factors into the process of technology adoption and usage. (Venkatesh, Brown, and Bala 2012). Within the UTAUT2 framework, performance expectancy and effort expectancy are consistently identified as central predictors of behavioral intention, highlighting users' expectations regarding productivity enhancement and ease of interaction. Empirical research on generative AI adoption similarly indicates that users are more likely to adopt AI tools when they perceive clear performance benefits and minimal effort requirements (Rana et al. 2024; Xu, Chen, and Zhang 2024).

However, findings related to other UTAUT2 constructs, particularly hedonic motivation and social influence, remain inconclusive. Some studies suggest that enjoyment, curiosity, and experiential value can encourage engagement with generative AI, especially in learning-oriented contexts (Kparl and Iddris 2024; Papathomas, Konteos, and Avlogiaris 2025). In contrast, other research reports that these factors play a limited role when generative AI is primarily used as a task-support tool rather than for recreational purposes (Cabero-almenara et al. 2024; Pasaribu and Widiyaningrum 2024). These mixed findings indicate that the drivers of generative AI adoption may vary depending on how users perceive the role of the technology in their activities.

Another limitation in the existing literature concerns the empirical context of prior studies. Research on generative AI adoption has predominantly focused on student samples or has been conducted in developed or cross-national settings. Although digital natives are often treated as a homogeneous group, emerging evidence suggests that adoption behavior is shaped by contextual factors such as digital infrastructure, access to technology, and informal usage practices (Creighton 2018). Studies examining generative AI adoption among broader groups of digital natives in emerging economies therefore remain limited, despite the rapid diffusion of these technologies in such contexts (Rana et al. 2024).

Addressing these gaps, the present study investigates the determinants of digital natives' behavioral intention to use generative artificial intelligence in an emerging economy context. Drawing on the UTAUT2 framework, this study focuses on performance expectancy, effort expectancy, social influence, and hedonic motivation as key explanatory variables. By examining these relationships among digital natives in Jakarta who have prior experience using generative AI, this research seeks to clarify inconsistent findings in previous studies and to provide a more context-sensitive understanding of generative AI adoption in voluntary, task-oriented digital environments.

2. LITERATURE REVIEW

The literature on generative artificial intelligence adoption has expanded rapidly alongside the diffusion of AI-based tools across academic and professional domains. This section reviews the theoretical and empirical foundations relevant to the study by first outlining the conceptualization of generative AI as a task-support technology, followed by a discussion of digital natives in voluntary technology use contexts. Next, the principal analytical framework that guides this study is the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2).

2.1 Theoretical and Conceptual Background

2.1.1 Generative Artificial Intelligence as a Task-Support Technology

Generative artificial intelligence refers to AI-based systems capable of producing original outputs—such as text, code, or visual content—by learning from large-scale datasets. Unlike traditional information systems that primarily support data processing or retrieval, generative AI tools are designed to augment human cognitive capabilities by assisting with complex tasks, including content creation, analysis, and decision-making (Feuerriegel and Janiesch 2024). As such, GenAI is increasingly conceptualized as a task-support technology that complements human effort rather than replacing it.

The voluntary and flexible nature of generative AI usage distinguishes it from many organizational information systems. Users independently decide whether, when, and how to integrate GenAI into their workflows, often experimenting with the technology across different tasks. Consequently, adoption is shaped less by formal requirements and more by subjective evaluations of usefulness, ease of use, and perceived value in specific contexts (Lv 2023). Behavioral intention therefore plays a pivotal role in explaining continued use and integration of generative AI tools.

2.1.2 Digital Natives and Voluntary Technology Use

Digital natives are commonly described as individuals who have grown up in environments saturated with digital technologies. While early studies often associated digital nativeness with inherent technological proficiency, more recent research cautions against viewing this group as uniformly inclined to adopt all emerging technologies (Creighton 2018). Instead, adoption decisions among digital natives are increasingly understood as being driven by perceived relevance, functional value, and task alignment rather than generational identity alone.

In voluntary usage contexts, digital natives tend to favor technologies that demonstrably enhance performance or reduce cognitive effort. Even among technologically experienced users, adoption is not automatic; it is contingent upon whether a technology meaningfully supports goal achievement. This perspective underscores the continued relevance of intention-based technology acceptance models, such as UTAUT2, for explaining generative AI adoption among digitally experienced populations.

2.1.3 Theoretical Framework Based on the UTAUT2 Model

The Unified Theory of Acceptance and Use of Technology (UTAUT) was developed by merging key components from several theories on technology adoption. These theories include the Technology Adoption Model, the Theory of Planned Behavior, and the Innovation Diffusion Theory (Venkatesh et al. 2003). According to the concept, behavioral intention is a major precursor of technology use, while social influence, performance expectation, and effort expectations are the primary drivers of technology use.

UTAUT2 extends this framework by incorporating motivational factors relevant to voluntary and consumer-oriented technologies, most notably hedonic motivation. This extension recognizes that adoption decisions may be shaped not only by utilitarian considerations but also by intrinsic enjoyment and experiential value. Given that generative AI tools are typically self-initiated and used flexibly, UTAUT2 provides a suitable analytical lens for examining intention-driven adoption in this context.

Rather than treating UTAUT2 as a static predictive model, recent studies increasingly employ it as a flexible framework that can be adapted to emerging technologies. In the case of generative AI, the framework allows researchers to examine how cognitive, motivational, and social evaluations jointly shape users' intentions, while remaining attentive to contextual variations.

2.2.1 Influence of UTAUT2 Constructs on Users' Behavioral Intention

An individual's behavioral intention reveals their deliberate readiness to embrace and sustain the use of a technology. When discussing generative AI, behavioral intention refers to the degree to which users are prepared to include AI technologies into the completion of professional and academic tasks. This research examines the factors that determine behavioral intention, specifically looking at performance expectation, effort expectancy, social influence, and hedonic motivation. It draws on the UTAUT2 framework and previous empirical evidence to support its claims.

Performance Expectancy

What people mean when they talk about "performance expectancy" is how much they think generative AI will improve their efficiency, effectiveness, and quality of work. When people believe that AI tools will make their lives easier by simplifying difficult or time-consuming jobs, they are more likely to use generative AI. This finding is supported by previous empirical research. (Cabero-almenara et al. 2024; Kim, Blazquez, and Oh 2024; Papathomas et al. 2025). Accordingly, higher perceived performance benefits are expected to strengthen users' intention to adopt generative AI.

H1: Performance expectancy positively influences behavioral intention to use generative artificial intelligence.

Effort Expectancy

How easy you think it will be to learn and use a technology is captured by effort expectation. Generative AI technologies may be more widely used if they include user-friendly interfaces and straightforward ways to engage with them. Even among users with extensive expertise with digital technologies, prior research has shown that the perception of ease of use is a strong predictor of the desire to embrace AI. (Rana et al. 2024; Xu et al. 2024).

H2: Effort expectancy positively influences behavioral intention to use generative artificial intelligence.

Social Influence

The degree to which people believe that influential people support the usage of a technology is a measure of its social impact. In the context of generative AI, social influence may originate from peers, instructors, or professional communities. While some studies report a positive effect of social influence on AI adoption intention, others suggest that its role diminishes as technologies become widely accessible and individually adopted (Cabero-almenara et al. 2024; Rana et al. 2024).

H3: Social influence has a positive effect on behavioral intention to use generative artificial intelligence.

Hedonic Motivation

Hedonic motivation refers to the intrinsic enjoyment derived from using a technology. In voluntary adoption contexts, enjoyment and curiosity may encourage initial engagement with generative AI tools. However, empirical findings remain mixed, with some studies indicating a significant role of hedonic motivation in learning-oriented settings, while others report limited influence when AI is primarily used for task completion rather than entertainment (Kparl and Iddris 2024; Papathomas et al. 2025).

H4: Hedonic motivation positively influences behavioral intention to use generative artificial intelligence.

3. RESEARCH METHODOLOGY

3.1 Research Design

The study used a quantitative research strategy based on a cross-sectional design to investigate what factors influence the behavioral intention to utilize generative AI among digital natives. We opted for a survey approach since it allows us to get all of the opinions and assessments on technology adoption from all of the respondents at once. Given that generative AI usage is largely voluntary and self-initiated, this design is appropriate for capturing intention-driven adoption behavior.

Using UTAUT2 as its foundation, this research seeks to explain how people use and accept technology. Partial Least Squares-Structural Equation Modeling (PLS-SEM) was used to examine the predicted connections between the

constructs. Research on emerging technologies often makes use of modest sample sizes, and this analytical approach is ideal for such studies because to its emphasis on prediction-oriented analysis, flexibility in dealing with non-normal data distributions, and suitability for such investigations.

3.2 Research Framework and Variables

The research framework conceptualizes the adoption of generative artificial intelligence as an intention-driven behavior. Behavioral intention serves as the endogenous variable, representing users’ willingness to continue using generative AI tools for academic and professional tasks. The study model incorporated four exogenous variables—performance expectancy, effort expectancy, social influence, and hedonic motivation—based on the UTAUT2 paradigm and past empirical results.

Performance expectancy reflects users’ perceptions of the extent to which generative AI enhances task performance and productivity. Effort expectancy represents perceived ease of use and clarity of interaction with AI tools. Social influence captures perceived social support or endorsement from important others, while hedonic motivation reflects intrinsic enjoyment associated with AI usage.

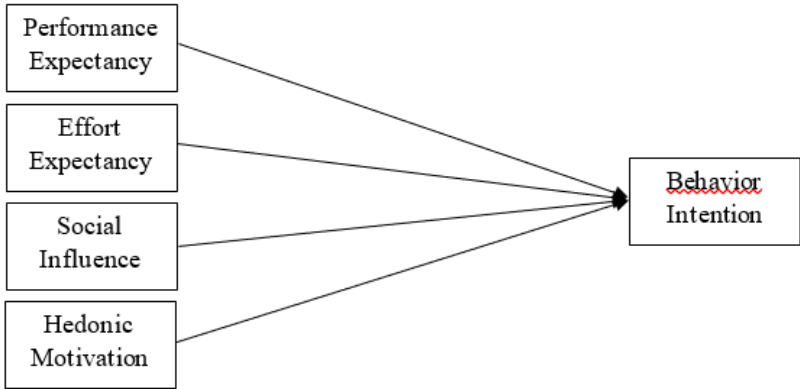


Figure 1. Research Framework
Source: Authors (2025)

Although facilitating conditions are conceptually part of the original UTAUT2 framework, this construct was excluded from the final research model. During the measurement model evaluation, one facilitating conditions indicator exhibited a substantially low outer loading (<0.40), and the remaining indicators failed to meet minimum reliability thresholds. Following established PLS-SEM guidelines, constructs that do not achieve acceptable measurement quality were removed to ensure model validity and interpretability (Hair et al. 2022). This decision reflects a methodological refinement rather than a theoretical dismissal of facilitating conditions.

3.3 Population, Sampling, and Data Collection

Digital natives living in Jakarta with expertise with generative AI technologies made up the population of this research. We used a purposive sample strategy to make sure that those who filled out the survey had enough knowledge of generative AI to provide us honest feedback on the study's variables. People defined as "digital natives" fall anywhere between the ages of 18 and 32.

Information was gathered by means of an online survey that was disseminated across digital mediums often accessed by young professionals and students. To make sure people have experience with generative AI before, we provided a screening question. Respondents were apprised of the study's goals before to filling out the questionnaire, and their participation was entirely voluntary. Respondents' anonymity was guaranteed since no individually identifying information was gathered.

3.4 Data Measurement

The measurement instruments were adapted from established UTAUT2-based studies and recent research on generative artificial intelligence adoption. All constructs were operationalized using reflective indicators, consistent with the theoretical assumptions of the UTAUT2 framework and common practice in PLS-SEM research. Measurement items were contextualized to reflect generative AI usage in academic and professional task settings while preserving their original conceptual meanings. The sources of the measurement items for each construct are summarized in table 1.

Constructs	Items	Sources
Performance Expectancy	PE1	The use of generative AI (e.g., ChatGPT, Gemini, and similar tools) helps me complete tasks more effectively.
	PE2	Generative AI (e.g., ChatGPT, Gemini, and similar tools) improves my productivity in completing tasks.
	PE3	By using generative AI (e.g., ChatGPT, Gemini, and similar tools), I can complete tasks more quickly.
		(Papathomas et al. 2025; Rana et al. 2024; Xu et al. 2024)

Constructs	Items	Sources
Effort Expectancy	EE1	(Kparl and Iddris 2024; Xu et al. 2024)
	EE2	
	EE3	
Social Influence	SI1	(Cabero-almenara et al. 2024; Kparl and Iddris 2024; Papathomas et al. 2025)
	SI2	
	SI3	
Hedonic Motivation	HM1	(Cabero-almenara et al. 2024; Papathomas et al. 2025; Rana et al. 2024)
	HM2	
	HM3	
Behavior Intention	BI1	(Kparl and Iddris 2024; Papathomas et al. 2025; Xu et al. 2024)
	BI2	
	BI3	

Table 1. Measurement Items

Source: Authors (2025)

All constructs were assessed using reflective indicators that were generated from well-established UTAUT2-based research. The replies were recorded using a five-point Likert scale, which ranges from strongly disagree to very agree. There was a two-step procedure taken to examine the data using SmartPLS software. Part of this strategy was checking how well the structural and measurement models worked together. To guarantee the study results were robust, reliability and validity were checked before hypothesis testing.

3.5 Data Analysis Procedure

Using SmartPLS software, a two-stage analytical process was used to undertake the data analysis. First, the measurement model was tested for convergent validity, discriminant validity, indicator reliability, and internal consistency reliability using HTMT, AVE, and composite reliability criteria. (Hair et al. 2022).

Using SmartPLS software, a two-stage analytical process was used to undertake the data analysis. External loadings, composite reliability, AVE, and HTMT criteria were used to evaluate the measurement model's indicator reliability, internal consistency reliability, convergent validity, and discriminant validity.

4. RESULT AND DISCUSSION

4.1 Result

4.1.1 Respondent Characteristics

A total of 152 participants who were considered digital natives and had some familiarity with GenAI technologies like Gemini and ChatGPT were surveyed for this research. Respondents are defined according to their age, gender, present situation, and length of time using generative AI.

In terms of age, the majority of respondents were in the 18–22 years age group, accounting for 41.9% of the total sample. This was followed by respondents aged 23–27 years (31.0%) and those aged 28–32 years (21.9%). Only a very small proportion of respondents were under 18 years old or above 32 years old. This distribution indicates that most respondents fall within the early productive age range, which is commonly associated with digital natives who are highly engaged with digital technologies.

Regarding gender, the sample was predominantly female, representing 69.7% of respondents, while male respondents accounted for 30.3%. This composition suggests higher participation among female respondents in this study on generative AI adoption, particularly within academic and professional contexts.

Based on current status, most respondents identified as students, comprising 40.6% of the sample. Respondents working as full-time employees accounted for 29.7%, while those engaged in part-time or freelance work represented 20.0%. The remaining 9.7% were respondents who were students while working. This distribution demonstrates that

the use of generative AI spans both academic and professional settings, highlighting its relevance across different user roles.

In terms of duration of generative AI usage, the largest proportion of respondents had been using generative AI for more than one year (39.6%), followed by those with 6–12 months of experience (38.3%). Respondents who had used generative AI for 3–6 months accounted for 20.8%, while users with less than three months of experience constituted only a minimal proportion. These findings indicate that most respondents possess relatively extensive experience with generative AI, enabling them to provide informed evaluations of the technology.

Overall, the respondent characteristics suggest that the sample is dominated by digital natives with substantial experience in using generative artificial intelligence for both academic and professional purposes. This supports the suitability of the respondents for examining factors that influence behavioral intention to use generative AI.

Measure	Item	Frequency	%
Gender	Male	45	30.3
	Female	107	69.7
	Total	152	100
Age (years)	Less than 18	2	1.3
	18-22	64	41.9
	23-27	47	31.0
	28-32	33	21.9
	Above 32	6	3.9
	Total	152	100
Current Status	Student	62	40.6
	Full-time Employee	45	29.7
	Part-time/Freelance	30	20.0
	Student with Employment	15	9.7
	Total	152	100
Length of GenAI Usage	Less than 3 months	1	0.6
	3-6 months	33	20.8
	6-12 months	58	38.3
	More than 1 year	62	40.8
	Total	152	100
Frequency of GenAI Use	Very Rare	2	1.3
	Rare	10	5.5
	Occasionally	27	17.4
	Often	77	51.0
	Very Often	36	23.9
	Total	152	100

Table 2. Respondent Demographics

Source: Authors (2025)

4.1.2 Measurement Model Results

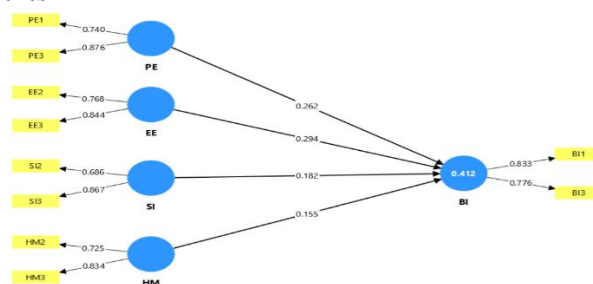


Figure 2. Measurement Model with Outerloading

Source: Authors (2025)

Indicator reliability, discriminant validity, convergent validity, and internal consistency reliability were examined to evaluate the measurement model. The PLS algorithm's outer loading values were used to assess the indicator's dependability. With the exception of SI2 (0.686), all indicators were higher above the suggested threshold of 0.70s. Since SI2 was found to have sufficient reliability and convergent validity, as well as having contributed to content validity, it was kept in accordance with PLS-SEM standards.

	Cronbach's Alpha	Composite Reliability (rho _a)	Composite Reliability (rho _c)	Average Variance Extracted (AVE)
BI	0.460	0.464	0.787	0.648
EE	0.466	0.475	0.788	0.651

HM	0.367	0.378	0.757	0.611
PE	0.489	0.522	0.792	0.657
SI	0.376	0.408	0.756	0.611

Table 3. Measurement Model Quality

Source: Authors (2025)

Internal consistency was evaluated primarily through composite reliability (CR). It is generally considered to be an improved statistic for PLS-SEM analysis compared to Cronbach's alpha. The experimental nature of the model and the small number of variables employed to quantify each construct likely account for the low Cronbach's alpha values. The findings demonstrate that all CR values above the suggested minimum threshold of 0.70, in line with the methodological guidelines of PLS-SEM, which emphasized composite dependability.

The AVE, or average variance extracted, was used to determine convergent validity. The results show that all of the constructs have AVE values more than 0.50, which means that they all meet the convergent validity condition (a construct must explain for more than half of the variation in its indicators).

	BI	EE	HM	PE	SI
BI					
EE	1.069				
HM	1.136	1.156			
PE	1.045	0.920	1.048		
SI	0.762	0.325	0.695	0.582	

Table 4. HTMT Matrix

Source: Authors (2025)

The heterotrait-monotrait (HTMT) ratio was used to evaluate discriminant validity. Despite the fact that several HTMT values were higher than the cautious cutoff of 0.90, especially among related UTAUT2 constructs, this finding has theoretical support. Bootstrapped HTMT confidence intervals, as suggested by Henseler et al. (2015), did not include the value of 1.0, confirming that discriminant validity was adequately established.

4.1.3 Structural Model Results

The assessment of the measurement model was finished before the hypotheses were tested using the structural model. We estimated path coefficients and used a bootstrapping approach with 5,000 resamples to evaluate the statistical significance of the correlations between the constructs.

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
EE -> BI	0.294	0.292	0.075	3.930	0.000
HM -> BI	0.155	0.158	0.088	1.751	0.080
PE -> BI	0.262	0.257	0.072	3.667	0.000
SI -> BI	0.182	0.189	0.092	1.991	0.047

Table 5. Path Coefficients & Hypothesis Testing

Source: Authors (2025)

Perceived ease of use is a key factor in encouraging digital natives to adopt generative AI technologies, as the study shows that effort expectation has a significant positive impact on behavioral intention ($\beta = 0.294$, $t = 3.930$, $p < 0.001$). Results show that behavioral intention is significantly influenced by performance expectation ($\beta = 0.262$, $t = 3.667$, $p < 0.001$), indicating that expected increases in performance are still a key factor in adoption.

Conversely, hedonic motivation does not show a statistically significant relationship with behavioral intention ($\beta = 0.155$, $t = 1.751$, $p = 0.080$), implying that enjoyment and intrinsic pleasure are not dominant factors influencing generative AI adoption in this context. Social influence, while statistically significant, exhibits a relatively modest effect on behavioral intention ($\beta = 0.182$, $t = 1.991$, $p = 0.047$), indicating that social encouragement plays a secondary role when compared to utilitarian considerations.

The explanatory capacity of the model was evaluated using the coefficient of determination (R^2). The R^2 value for behavioral intention is 0.412, which indicates that the exogenous variables account for 41.2% of the variance in behavioral intention. This level of explanatory power can be considered moderate within behavioral research.

Further analysis of effect sizes (f^2) shows that effort expectancy contributes the strongest effect on behavioral intention, followed by performance expectancy, whereas hedonic motivation and social influence display relatively small effect sizes. Predictive relevance was assessed using the PLSpredict procedure, yielding a Q^2 predict value of 0.358 for behavioral intention. As this value exceeds zero, the model demonstrates adequate predictive relevance.

4.2 Discussion

This study aimed to examine the determinants of digital natives' behavioral intention to use generative artificial intelligence by applying the UTAUT2 framework. Overall, the findings indicate that generative AI adoption among digital natives in Jakarta is primarily driven by utilitarian considerations, particularly perceived ease of use and

perceived performance benefits. These results suggest that generative AI is largely viewed as a functional tool that supports task completion rather than as a source of enjoyment or social expression.

Performance Expectancy

The significant effect of performance expectancy highlights the importance of perceived productivity gains in shaping behavioral intention. Generative AI tools are often used to support tasks such as writing, information synthesis, and problem-solving. Users are more likely to keep utilizing generative AI if they believe these technologies improve the quality and efficiency of their work. Consistent with other research, this conclusion highlights the importance of perceived utility in the voluntary adoption of technology.

Effort Expectancy

Similarly, the significant influence of effort expectancy suggests that digital natives are more likely to adopt generative AI when the technology is perceived as easy to learn and operate. Despite their high level of digital familiarity, digital natives still value technologies that minimize cognitive effort and integrate seamlessly into their existing workflows. This finding supports prior research indicating that usability remains a critical determinant of AI adoption, even among technologically experienced users.

Hedonic Motivation

In contrast, hedonic motivation was found to be non-significant, indicating that enjoyment is not a decisive factor in generative AI adoption among digital natives in this study. It seems from this outcome that generative AI is more often seen as a practical tool than as something to be entertained with. Generative AI seems to be adopted more for its practical utility than for its pure delight, as it becomes more enmeshed in academic and professional activity.

Social Influence

The effect of social influence, although statistically significant, is relatively weak. This suggests that adoption decisions among digital natives are largely autonomous and less dependent on social pressure or peer endorsement. The widespread availability and normalization of generative AI tools may reduce the importance of social influence, as users rely more on personal evaluations of utility and ease of use.

5. CONCLUSION

This study examined the determinants of digital natives' behavioral intention to use generative artificial intelligence by applying the UTAUT2 framework in an emerging economy context. The findings indicate that adoption decisions are primarily driven by utilitarian considerations, particularly perceived ease of use and perceived performance benefits.

Digital natives are more inclined to embrace generative AI if they believe it will enhance task performance and is simple to use, according to research that revealed performance expectation and effort expectancy to be major determinants of behavioral intention. Rather from being seen as a source of entertainment, these findings show that generative AI is primarily assessed as a tool to increase productivity.

Hedonic motivation, on the other hand, failed to have any discernible impact on planned actions. In academic and professional settings that focus on tasks, this study implies that intrinsic pleasure has a limited impact on the adoption of generative AI. Individual assessments, not societal pressure, seem to have a larger role in adoption choices, since social influence had a statistically significant but little impact.

By drawing attention to a change toward utilitarian adoption logic within the framework of sophisticated AI technologies, this research adds theoretical weight to the literature on technology adoption. While UTAUT2 traditionally incorporates both utilitarian and hedonic dimensions, the findings suggest that the relative importance of these constructs may change as technologies become embedded in routine task execution.

Several limitations should be acknowledged. This study focused on digital natives in a single geographic area and examined behavioral intention rather than actual usage behavior. Future research is encouraged to employ longitudinal designs and to incorporate additional variables, such as trust, perceived risk, or ethical considerations, to provide a more comprehensive understanding of generative AI adoption.

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