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RESEARCH ARTICLE

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Examining the Impact of Digital Technologies on the Generative Artificial Intelligence Integration of Businesses in Türkiye

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Abstract

Generative Artificial Intelligence (GenAI), which can autonomously produce textual, visual, auditory, and video content, goes beyond creativity and offers significant advantages in business processes. This study aims to examine the relationship between the digital processes used in firms and employees' levels of artificial intelligence usage and their intention to use it, within the framework of four fundamental factors of GenAI: performance expectancy, effort expectancy, facilitating conditions, and social influence. Data were collected from employees working in 213 companies operating in Türkiye and analyzed using regression analysis and Pearson correlation methods. The findings indicate that the digital processes implemented in firms do not have a statistically significant effect on these four factors. In contrast, employees' intention to use artificial intelligence has a significant and positive effect on performance expectancy and social influence. Moreover, the current use of artificial intelligence is found to create significant and positive effects on effort expectancy, facilitating conditions, and social influence. Overall, the results demonstrate that, rather than the quantitative presence of digital processes, employees' attitudes and tendencies toward artificial intelligence play a more decisive role in the integration of generative AI.

Keywords: *Generative Artificial Intelligence, Digital Process, Artificial Intelligence Usage*

Öz

Metin, görsel, işitsel ve video içeriklerini özerk biçimde üretebilen üretken yapay zekâ (ÜYZ), yalnızca yaratıcılıkla sınırlı kalmayıp iş süreçlerinde de önemli avantajlar sunmaktadır. Bu çalışma, firmalarda kullanılan dijital süreçler ile çalışanların yapay zekâ kullanım düzeyleri ve yapay zekâ kullanım niyetleri arasındaki ilişkiyi; ÜYZ'ye ilişkin dört temel faktör — performans beklentisi, çaba beklentisi, kolaylaştırıcı koşullar ve sosyal etki — bağlamında incelemeyi amaçlamaktadır. Araştırma kapsamında, Türkiye'de faaliyet gösteren 213 firmada çalışanlardan elde edilen veriler regresyon analizi ve Pearson korelasyon yöntemleriyle değerlendirilmiştir. Analiz sonuçlarına göre, firmalarda kullanılan dijital süreçlerin söz konusu dört faktör üzerinde anlamlı bir etkisi bulunmamaktadır. Buna karşılık, çalışanların yapay zekâ kullanma niyetleri performans beklentisi ve sosyal etkiyi anlamlı ve pozitif yönde etkilemektedir. Ayrıca, mevcut yapay zekâ kullanımının çaba beklentisi, kolaylaştırıcı koşullar ve sosyal etki üzerinde anlamlı ve olumlu etkiler yarattığı görülmektedir. Sonuçlar, dijital süreçlerin niceliksel varlığından ziyade çalışanların yapay zekâya yönelik tutum ve eğilimlerinin, üretken yapay zekâ entegrasyonunda belirleyici olduğunu göstermektedir.

Anahtar Kelimeler: *Üretken Yapay Zekâ. Dijital Süreçler, Yapay Zekâ Kullanımı.*

Review Note: *Evaluated by Double-Blind Peer Review*

Ethical Statement: *Ethical matters may be addressed via editorialoffice@opusjournal.net*

Introduction

Recently, Generative Artificial Intelligence (GenAI) has become a prominent field of study in the business world. With the global proliferation of digital technologies, including AI, organizations face increasing pressure to embrace these innovations and restructure operations in line with Industry 4.0 (Lindberg, 2025). GenAI, intended to produce complex material, is used in many fields (Cao et al., 2023; Dwivedi et al., 2023; Kasneci et al., 2023) and can significantly alter teaching and learning approaches (Megahed et al., 2023). It improves efficiency, drives creativity, and generates economic benefits across industries (Ali et al., 2025).

Using user instructions, GenAI creates text and picture material (Lim et al., 2023; Wu et al., 2023). Gupta and Srivastava (2024) note that GenAI is a paradigm shift characterized by its ability to innovate beyond and create new datasets. While AI mimics human intelligence broadly, GenAI focuses on producing original content like language, music, or images (Lim et al., 2023). OpenAI debuted Voice Engine in March 2024, generating natural-sounding speech with minimal input (OpenAI, 2024). GPT-4o, released in May 2024, expanded GenAI's multimodal applications across industries.

GenAI is a disruptive technology gaining a large user base due to human-like responses and ease of use. It benefits businesses through productivity, efficiency, and competitive advantage (Ünal and Kılınç, 2024). Adoption in business is increasing, but academic research is still limited. Existing studies are largely theoretical (Bozkurt, 2023; Avcı, 2024; Ünal and Kılınç, 2024), with few firm-level analyses.

There is a stream of literature investigating acceptance intention to continue using GenAI. Ali et al. (2023) found IT infrastructure, R&D, and corporate investment facilitate adoption, while inconsistent policies hinder it. Dong et al. (2024) emphasized organizational listening and readiness. Kumar (2025) surveyed 277 executives, highlighting information integrity, transparency, and ethical leadership. Rana et al. (2024) studied institutional pressures and principles like accuracy and fairness. Chan and Choi (2025) classified GenAI applications in marketing. Kong et al. (2024) surveyed 367 Hong Kong teachers, showing attitudes and perceived usefulness drive GenAI use. Dogru et al. (2025) explored advantages and limitations in tourism, while Gursoy et al. examined ChatGPT in hospitality. GenAI is also applied in healthcare (Zhang and Kamel Boulos, 2023), education (BaidooAnu and Ansah, 2023), marketing (Kshetri et al., 2023), banking (Sleiman, 2023), and fashion (Harreis et al., 2023).

This research aims to explore how the digital technologies implemented within organizations relate to AI applications and orientations, as well as employees' perceptions of GenAI usage, focusing on performance expectancy, facilitating conditions, effort expectancy, and social influence. The research aims to enrich the existing literature by addressing this gap through a regression analysis of survey data collected from employees working in diverse companies. Specifically, it examines the relationship between the digital technologies utilized in business processes, employees' current use of artificial intelligence, and their willingness to adopt AI—key components of generative AI innovation. Furthermore, the study investigates how factors such as performance expectancy, facilitating conditions, effort expectancy, and social influence align with generative AI adoption. Drawing on the findings, the study ensures actionable recommendations for organizations aiming to improve their adoption and integration of generative AI technologies.

The paper is structured as follows: the theoretical framework, methodology and data collection, findings, and conclusion.

Theoretical Framework

This section presents the study's conceptual framework, including an overview of GenAI and its types.

Generative AI (GenAI): GenAI generates text, images, audio, and video from multimodal input data (Bengesi et al., 2023) and is expected to enhance business processes, customer interactions, and innovation across industries like entertainment, manufacturing, and healthcare (Ooi et al., 2023; Kar et al., 2023; Lv, 2023).

Large Language Models (LLMs): LLMs like GPT-3 and GPT-4 are deep learning models pre-trained on large datasets to understand and generate human-like language, supporting tasks such as text generation, summarization, translation, decision-making, and content creation (OpenAI, 2024).

AI Content Tools: AI-driven content tools create written material with minimal human input using machine learning and NLP, widely used in marketing, social media, and professional writing, offering multilingual support and SEO optimization (Gao et al., 2023).

AI Image Generation: Techniques like GANs and CAN generate realistic visuals with minimal human input, transforming digital art, design, and corporate visual content creation (Elgammal et al., 2017).

AI Voice Generation: AI speech technologies enable text-to-speech, voice transfer, and cloning, enhancing virtual assistants, audiobooks, accessibility, and user experience (Miniota et al., 2023).

AI Video Generation: AI video tools streamline creation and editing, supporting content creators in education, entertainment, and media production (Shibuya et al., 2025).

Methods

The study universe comprised companies in Türkiye, with employees from 213 companies sampled. Sample size was determined using G*Power (v3.1.9.4), requiring at least 84 observations for correlations (α = 0.05, power = 0.8), so the actual sample exceeded this minimum.

Multiple sampling methods were employed: snowball sampling via WhatsApp (Biernacki & Waldorf, 1981) for hard-to-reach participants, complemented by convenience and simple random sampling to improve accessibility and representativeness (Etikan, Musa, & Alkassim, 2016; Field, 2005).

The study employed descriptive, exploratory, and correlational methods. The descriptive method identifies the current state of AI in businesses, including usage extent, sectors, areas, and willingness for adoption. The exploratory method seeks deeper insights, while the relational method examines relationships between Digital Processes, Desire for AI Use, AI Use, and Generative AI Use. In addition to descriptive and exploratory approaches, regression analysis was employed to examine the relationships between Digital Processes, Desire for AI Use, AI Use, and Generative AI Use within the scope of Generative AI factors. This analysis provided deeper insights into the predictive and explanatory power of these variables, revealing the extent to which digital transformation processes and organizational intentions shape the adoption and utilization of generative AI technologies.

The survey was the main data collection instrument. The first section included 15 demographic questions and items about digital processes (e.g., CRM, ERP, RPA, inventory tracking). From these, the variable "digital technology usage" was created. Similarly, questions on AI applications (e.g., chatbots, customer segmentation, product recommendations, profitability analysis, demand estimation, and customer satisfaction) formed the "AI Use" variable. The number of responses to “Subjects where AI would be useful” created the "AI Usage Desire" variable.

In the second section, 20 items measured the use of generative AI in businesses, with 7 items for “Performance Expectancy,” 5 for “Effort Expectancy,” 3 for “Facilitating Conditions,” and additional questions on “Social Influence,” rated on a 5-point Likert scale. The “Generative Artificial Intelligence Acceptance Scale” by Yilmaz et al. (2023) was used to assess adaptation to generative AI in Türkiye.

Table 1. Factors and Items

Factor Number	Factor Name	Number of Questions
1	Performance Expectancy	7
2	Effort Expectancy	5
3	Facilitating Conditions	3
4	Social Influence	5

Ethical Approval, Survey Instrument, and Data Collection

This study was approved by the Istanbul Medipol University Social Sciences Ethics Committee (20.01.2025-17637). Participants were Turkish citizens over 18, limited to one response per person via Google account verification. Data were collected anonymously using Google Forms, with consent obtained prior to participation, and processed in R Studio. Snowball and convenience sampling were employed, contacting participants via WhatsApp without public sharing to ensure authenticity. Snowball sampling addressed difficulties in accessing the full population (Patton, 2014). Following social science guidelines (Field, 2005; Gorsuch, 1974), 213 responses were collected between October 10 and November 31, 2024.

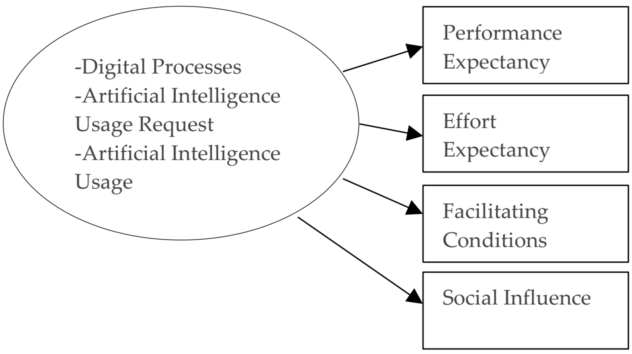

Figure 1. Research Model

Research Hypotheses are shown below:

H1: There is a significant relationship between Digital Processes and Performance Expectancy.

H2: There is a significant relationship between Artificial Intelligence Usage Desire and Performance Expectancy.

H3: There is a significant relationship between Artificial Intelligence Usage and Performance Expectancy.

H4: There is a significant relationship between Digital Processes and Effort Expectancy.

H5: There is a significant relationship between Artificial Intelligence Usage Desire and Effort Expectancy.

H6: There is a significant relationship between Artificial Intelligence Usage and Effort Expectancy.

H7: There is a significant relationship between Digital Processes and Facilitating Conditions.

H8: There is a significant relationship between Artificial Intelligence Usage Desire and Facilitating Conditions.

H9: There is a significant relationship between Artificial Intelligence Usage and Facilitating Conditions.

H10: There is a significant relationship between Digital Processes and Social Influence.

H11: There is a significant relationship between Artificial Intelligence Usage Desire and Social Influence.

H12: There is a significant relationship between Artificial Intelligence Usage and Social Influence.

Findings

This section presents the demographic characteristics of employees and the main results.

Demographic Frequency Analyses

Table 2 summarizes the demographic distribution of employees by gender, age, education level, marital status, and professional experience, reported as frequencies and percentages.

Table 2. Demographic Istatistics of Participant- Descriptive Statistics

Gender	**Frequency (N=213)**	**%**
Male	141	66,2
Female	72	33,8
Age	**Frequency (N=213)**	**%**
< 24	47	22,07
25-34	122	57,28
35-44	35	16,43
45-54	9	4,23
Education Level	**Frequency (N=213)**	**%**
Bachelor's degree	155	72,77
High School	5	2,35
Master's degree	29	13,62
Vocational School	24	11,27
Job	**Frequency (N=213)**	**%**
Junior Manager	14	6,57
Company Owner	10	4,69
Operational Manager	15	7,04
Middle Manager	32	15,02
Professional Employee	129	60,56
Senior Manager	13	6,1
Years of Working in the Company	**Frequency (N=213)**	**%**
< 1	58	27,23
1-5	116	54,46
5-10	25	11,74
10-15	14	6,57

Total Years of Work	**Frequency (N=213)**	**%**
< 1	24	11,27
1-5	85	39,91
5-10	43	20,19
10-15	32	15,02
> 15	29	13,62
Company Size	**Frequency (N=213)**	**%**
1-5	14	6,57
5-9	32	15,02
10-49	40	18,78
50-249	39	18,31
> 250	120	56,34
Company Sector	**Frequency (N=213)**	**%**
Banking/Finance	13	6,1
Service	47	22,07
Retail	9	4,23
Industry	28	13,15
Trade	13	6,1
Transportation	7	3,29
Software or IT Solutions	84	39,44

The participants were 33.8% female and 66.2% male. Most were aged 25–34 (52.28%), followed by under 24 (22.07%) and 35–44 (16.43%). Regarding education, 72.77% held a bachelor's, 13.62% a master's, and 11.27% an associate degree. In organizational roles, 60.56% were professional staff and 15.02% mid-level managers. Tenure showed 54.46% with 1–5 years, 27.23% less than one year, and 11.74% with 5–10 years. For total work experience, 39.91% had 1–5 years, 20.19% had 5–10 years, and 15.02% had 10–15 years. By company size, 56.34% worked in firms with 250+ employees, 18.78% in firms with 10–49 employees, and 18.31% in firms with 50–249 employees. Sectoral distribution showed 39.44% in software/IT, 22.07% in services, and 13% in industry.

Table 3. Variance Values of Questions

Question	Variance	Question	Variance
Q1	0,637	Q11	0,597
Q2	0,749	Q12	0,572
Q3	0,663	Q13	0,716
Q4	0,806	Q14	0,793
Q5	0,588	Q15	0,673
Q6	0,623	Q16	0,842
Q7	0,567	Q17	0,895
Q8	0,562	Q18	0,826
Q9	0,593	Q19	0,862
Q10	0,619	Q20	0,862

The variance values for each question are shown in Table 3.

Validity and Reliability Analyses

Study validity was assessed with the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test of sphericity, and reliability with Cronbach's alpha coefficient.

Validity

Construct validity was assessed using exploratory factor analysis with principal components analysis. KMO values were 0.917, 0.873, and 0.712 for Performance Expectancy, Effort Expectancy, and Facilitating Conditions & Social Influence, indicating adequacy, and Bartlett's test was significant ($p < 0.01$), confirming factor analysis suitability.

Table 4. KMO and Bartlett's Tests Analysis

		Performance Expectancy	Effort Expectancy	Facilitating Conditions	Social Influence
KMO Measure of Sampling Adequacy		0,917	0,873	0,689	0,872
Bartlett's of Sphericity	Chi-square	1206,665	854,612	228,799	846,013
	Df	21	10	3	10
	Sig.	0,000	0,000	0,000	0,000

Reliability

The Cronbach's alpha coefficient is a commonly used metric for evaluating the reliability and internal consistency of measurement scales (Alpar, 2020). According to correlation coefficient interpretation guidelines, the relationships between variables are classified as low (0–0.29), moderate (0.30–0.64), strong (0.65–0.84), and very strong (0.85–1.00). (Ural and Kılıç, 2021).Using Cronbach's Alpha (σ_x^2) (Cohen, 1988) is a way to examine reliability using the following equation:

$$\rho_T = \frac{k}{k-1}\left(1 - \frac{\sum_{i=1}^{k} \sigma_i^2}{\sigma_x^2}\right) \qquad (1)$$

Here, k represents the number of questions using the Likert scale (20 questions in the survey). For each question, variances were calculated as listed in Table 2. Then, the sum of the variances called σ_x^2 was calculated as 14.0531. Cronbach's α was calculated for all factors using Equation (1).

The reliability analysis of the scales used in the study is illustrated in Table 5.

Table 5. Cronbach Alpha values of factors

Factor	Cronbach's Alpha	Number of Questions
Performance Expectancy	0,938	7
Effort Expectancy	0,927	5
Facilitating Conditions	0,813	3
Social Influence	0,926	5

The minimum acceptable threshold for Cronbach's Alpha reliability coefficient is generally considered to be 0.81. The Performance Expectancy scale demonstrated a Cronbach's alpha of 0.938, reflecting excellent internal consistency and high reliability. Furthermore, across all individual items, Cronbach's alpha values ranged from 0.81 to 1.00, indicating that the scale items exhibit consistently high reliability.

Table 6. The Mean, standart deviation, skewness and kurtosis values of each questions for the study.

Variable	Item	Mean	SD	Skewness	Kurtosis
Performance Expectancy	Q1	4,281	0,798	-1,272	5,188
	Q2	4,122	0,865	-1,112	4,510
	Q3	4,220	0,814	-1,158	4,763
	Q4	4,098	0,897	-1,095	4,382
	Q5	4,300	0,767	-1,322	5,724
	Q6	4,234	0,789	-1,131	4,898
	Q7	4,201	0,753	-0,747	3,322
Effort Expectancy	Q8	4,178	0,749	-0,773	3,900
	Q9	4,140	0,770	-0,742	3,707
	Q10	4,089	0,786	-0,681	3,506
	Q11	4,173	0,772	-0,984	4,741
	Q12	4,112	0,756	-0,779	4,037
Facilitating Conditions	Q13	4	0,846	-0,700	3,503
	Q14	3,938	0,890	-0,763	3,563
	Q15	4,032	0,820	-0,727	3,733
Social Influence	Q16	3,826	0,917	-0,641	3,177
	Q17	3,751	0,946	-0,759	3,667
	Q18	3,755	0,909	-0,669	3,386
	Q19	3,760	0,928	-0,713	3,466
	Q20	3,7417	0,928	-0,707	3,437

Table 6 reports the mean, standard deviation, skewness, and kurtosis values. Skewness (−0.641 to −1.322) and kurtosis (3.177 to 5.188) fall within acceptable limits (Kline, 2023), confirming normal distribution. Item means ranged from 3.386 to 4.300 with standard deviations between 0.637 and 0.946, indicating favorable attitudes and low variability. Participants particularly agreed that Generative AI enhances performance (Q5: M = 4.30, SD = 0.897) and is easy to adopt (Q8: M = 4.18, SD = 0.80).

Correlation Analysis

Before hypothesis testing, Pearson correlation analysis was conducted to examine relationships among study dimensions (Table 7).

Table 7. Correlation analysis

	Performance Expectancy	Effort Expectancy	Facilitating Conditions	Social Influence
Performance Expectancy	1	0,630	0,520	0,535
Effort Expectancy	0,630	1	0,623	0,428
Facilitating Conditions	0,520	0,623	1	0,506
Social Influence	0,535	0,42806477	0,506	1

Correlation analysis showed significant positive relationships among the scales ($p < 0.05$). Performance Expectancy strongly correlated with Effort Expectancy ($r = 0.630$) and moderately with Facilitating Conditions ($r = 0.520$) and Social Influence ($r = 0.535$). Effort Expectancy correlated with Facilitating Conditions ($r = 0.623$) and Social Influence ($r = 0.428$), while Facilitating Conditions and Social Influence also correlated ($r = 0.506$), indicating interrelated perceptions.

Regression Analysis

A multivariate regression examined the causal relationships and the effects of independent variables—Digital Processes, Desire to Use Artificial Intelligence, and Artificial Intelligence Usage—on dependent variables: Performance Expectancy, Effort Expectancy, and Facilitating Conditions and Social Influence. Stepwise regression retained only independent variables with a statistically significant influence on performance expectancy.

Digital technology use in firms was coded as 1 for 'yes' and 0 for 'no'. Results showed ChatGPT had a significant positive effect on all four GenAI dependent variables (Table 8), suggesting it is the most impactful technology. Other technologies—CRM, ERP, and HR software—were non-significant ($p > 0.05$).

Table 8. The Relationship between ChatGPT Usage and performance expectancy

Performance Expectancy	Beta	Sig.
ChatGPT	0,21	0,0039
Adj. R2	0,09460924	
N	213	
F	2,110	
Sig.	0,0039	
Durbin-Watson	1,894	
Standard Error	0,077	

The results in Table 8 were obtained in a single step using the stepwise method in the Multivariate Regression Analysis. All digital processes except ChatGPT were found to have no significant effect on the Performance Expectancy factor ($p>0.05$). Thus, these variables were not included in the model. ChatGPT use, however, has a significant and positive effect on Performance Expectancy. Therefore, it can be argued that employees' performance will improve as their ChatGPT use increases. The extent of this variable's impact can be decided by looking at the R2 value. The R2 value is 0.094, or 9.4%. ChatGPT use explains 9.4% of performance expectancy. This is a very low percentage. Based on this, it can be concluded that ChatGPT use has a negligible effect on performance expectancy.

Table 9. The Relationship between ChatGPT Usage and Effort Expectancy

Effort Expectancy	Beta	Sig.
ChatGPT	0,199	0,0057
Adj. R2	0,10282900	
N	213	
F	2,315	
Sig.	0,00572130	
Durbin-Watson	2,120	
Standard Error	0,071	

Table 9 shows that only ChatGPT use had a significant positive effect on Effort Expectancy ($p > 0.05$), while other digital processes were non-significant and excluded from the model. The R^2 value is 0.10, indicating that ChatGPT explains 10% of the variance, suggesting a modest and not decisive effect on Effort Expectancy.

Table 10. The Relationship between ChatGPT Usage and Facilitating Conditions

Facilitating Conditions	Beta	Sig.
ChatGPT	0,28	0,000098
Adj. R2	0,13033602	
N	213	
F	3,0274	
Sig.	0,000098	
Durbin-Watson	2,0848	
Standard Error	0,0704	

Table 10 shows a significant positive relationship between ChatGPT use and Facilitating Conditions ($p < 0.05$), indicating that higher usage improves perceptions of supportive resources. The model's $R^2 = 0.13$, showing a modest effect, suggesting other contextual and organizational factors also influence this dimension.

Table 11. The Relationship between ChatGPT and ERP Usage with Social Pressure

Social Pressure	Beta	Sig.
ChatGPT	0.1995	0,001798735
ERP	0,1336	0,03063285
Adj. R2	0,192881176	
N	213	
F	1,9236	
Durbin-Watson	2,110	
Standard Error	0,0722	

Table 11 shows ChatGPT and ERP have significant positive effects on Social Influence ($p < 0.05$), indicating increased usage enhances perceived social pressure. The model's $R^2 = 0.19$, suggesting a modest impact and that other factors likely contribute.

Table 12. The Relationship between artificial intelligence use request and performance expectancy

Performance Expectancy	Beta	Sig.
Request for Artificial Intelligence Use	0.065	0.0003
Adj. R2	0.058	
N	213	
F	13,16	
Sig.	0.0003	
Durbin-Watson	1,916	
Standard Error	0.01807	

In stepwise multivariate regression (Table 12), digital processes and AI usage were non-significant ($p > 0.05$) and excluded. AI Usage Desire had a significant positive effect on Performance Expectancy, with adjusted $R^2 = 0.058$, explaining 5.8% of its variance, indicating a weak effect.

Table 13. The Relationship between artificial intelligence use and effort expectancy

Effort Expectancy	Beta	Sig.
Artificial Intelligence Use	0,070	0,0009
Adj. R2	0,050	
N	213	
F	11,186	
Sig.	0,0009	
Durbin-Watson	2,110	
Standard Error	0,021	

Table 13 shows that Digital Processes and AI Usage Desire were non-significant ($p > 0.05$) and excluded. AI Usage had a significant positive effect on Effort Expectancy, with adjusted $R^2 = 0.050$, explaining about 5% of its variance, indicating a modest effect.

Table 14. The Relationship between artificial intelligence use and effort expectancy

Facilitating Conditions	Beta	Sig.
Artificial Intelligence Use	0,086	0,00016
Adj. R2	0,0652	
N	213	
F	14,717	
Sig.	0,00016	
Durbin-Watson	2,101	
Standard Error	0,022	

Table 14 shows Digital Processes and AI Usage Desire were non-significant ($p > 0.05$) and excluded. AI Usage positively affected Facilitation, with adjusted $R^2 = 0.065$, explaining 6.5% of the variance, indicating a negligible effect.

Table 15. Relationship between artificial intelligence use and social pressure

Social Pressure	Beta	Sig.
Artificial Intelligence Use	0,071	0.00696
Request for Artificial Intelligence Use		0.02231
Adj. R2	0,077	
N	213	
F	8,882	
Sig.	0,022	
Durbin-Watson	2,091	
Standard Error	0,026	

Table 15 shows Digital Processes and AI Usage Desire were non-significant ($p > 0.05$) and excluded. AI Usage positively affected Facilitating Conditions, with adjusted $R^2 = 0.065$, explaining 6.5% of the variance, indicating a weak effect.

The acceptance or rejection of the hypotheses based on the analysis results is summarized in Table 16.

Table 16. Hypothesis testing results

Hypothesis	Result
H1: There is a significant relationship between Digital Processes and Performance Expectancy.	Rejected
H2: There is a significant relationship between Artificial Intelligence Usage Desire and Performance Expectancy.	Accepted
H3: There is a significant relationship between Artificial Intelligence Usage and Performance Expectancy	Rejected
H4: There is a significant relationship between Digital Processes and Effort Expectancy.	Rejected
H5: There is a significant relationship between Artificial Intelligence Usage Desire and Effort Expectancy.	Rejected
H6: There is a significant relationship between Artificial Intelligence Usage and Effort Expectancy.	Accepted
H7: There is a significant relationship between Digital Processes and Facilitating Conditions.	Rejected
H8: There is a significant relationship between Artificial Intelligence Usage Desire and Facilitating Conditions.	Rejected
H9: There is a significant relationship between Artificial Intelligence Usage and Facilitating Conditions.	Accepted
H10: There is a significant relationship between Digital Processes and Social Influence.	Rejected
H11: There is a significant relationship between Artificial Intelligence Usage Desire and Social Influence.	Accepted
H12: There is a significant relationship between Artificial Intelligence Usage and Social Influence.	Accepted

Conclusion

During early digital transformation, many companies began integrating GenAI to enhance strategic planning and decision-making. However, research on GenAI's impact on consumer-oriented business practices is limited. As GenAI develops, it is expected to improve organizational performance and workflows, making it crucial to understand employee attitudes and decision-making tendencies prior to implementation.

This study analyzed digital technology use, existing AI adoption, and employee demand for AI in 213 Turkish firms across four dimensions: performance expectancy, effort expectancy, facilitating conditions, and social influence. Results indicate that tools like RPA, CRM, and Inventory Tracking Automation had no significant effect on GenAI adoption dimensions, except ChatGPT, which showed a consistent positive impact. ERP affected only social influence. AI-specific tools, such as chatbots, recommendation systems, and analytics, positively influenced effort expectancy, facilitating conditions, and social influence, while employees' desire to use AI increased performance expectancy and social influence.

The study highlights that the number of digital tools alone does not ensure GenAI readiness; digital maturity, integration, usage intensity, and process efficiency, along with employee attitudes, are key factors. Limitations include sample concentration in IT and large firms, non-probability sampling, simplified process measures, and low model explanatory power.

Discussion and Limitations

Although the results of this study offer valuable insights, some limitations should be considered, particularly regarding the generalizability of the results, sample limitations, variable measurement methods, low R^2 values, and the ineffectiveness of digital processes. A large proportion of participants were from the IT sector (39.44%) and large enterprises (56.34%), limiting the generalizability of the findings to other industries and smaller firms. Low participation from SMEs and less digitally advanced sectors may underrepresent sector-specific challenges and GenAI adoption potential. Adoption patterns of digital technologies and AI can vary by industry and firm size (Vargo & Lusch, 2017; Yoo, Henfridsson, & Lyytinen, 2010), highlighting the need for sectoral diversity. Despite non-significant ANOVA results across sectors or firm sizes, skewed sample distribution calls for cautious interpretation.

The study's sample was collected via snowball, convenience, and simple random sampling, with overrepresentation of IT and large enterprises, which may introduce selection bias (Biernacki & Waldorf, 1981; Patton, 2014). Future research should use more comprehensive digital maturity models and representative samples, assessing not only the number of technologies but also integration depth, usage intensity, effectiveness, and process efficiency.

Although the gender distribution of participants in this study is imbalanced (66.2% male, 33.8% female), independent sample t-tests indicated that there were no statistically significant differences in GenAI-related perceptions or usage between male and female respondents. Therefore, gender was not included as a control variable in the regression analyses. Moreover, the unit of analysis in this study focuses primarily on firm-level GenAI usage rather than individual-level preferences, as responses reflect the use and adoption of GenAI tools within organizations. While gender-based behavioral differences may exist in broader technology adoption contexts, the current findings suggest that in the organizational setting of this study, gender did not exert a meaningful influence. Nonetheless, future research with more balanced samples could explore potential moderating effects of gender in greater detail.

The study primarily used snowball sampling, suitable for hard-to-reach populations or when population information is limited (Patton, 2014). While effective, this method can introduce bias and homogenization (Biernacki & Waldorf, 1981). To reduce these limitations and enhance diversity, participants were also recruited via convenience and simple random sampling, improving the study's reliability and validity.

A key limitation of this study is that "Digital Processes," "AI Use," and "AI Use Intention" were measured using simple counts or binary coding, which do not capture the depth, frequency, integration, or strategic importance of technology adoption. This limits the explanatory power of the findings. Future research should use multidimensional measures—such as composite indices of usage, integration, user satisfaction, and impact—and qualitative methods like interviews or case studies to better assess AI adoption and sectoral differences. Likert-type scales can also capture variations in AI usage desire across organizational contexts.

The adjusted R^2 values obtained from the regression models examining the relationships between AI usage, AI adoption intention, and GenAI usage are relatively low (Performance Expectancy: 0.058; Effort Expectancy: 0.050; Facilitating Conditions: 0.065; Social Influence: 0.077). Similarly, the adjusted R^2 values from the regression model that used Digital Technology adoption as a binary variable (present=1, absent=0) are also low (Performance Expectancy: 0.095; Effort Expectancy: 0.103; Facilitating Conditions: 0.130; Social Influence: 0.193). The relatively low adjusted R^2 values observed in the regression models highlight the limited explanatory power of the current set of independent variables in accounting for variations in Generative AI (GenAI) adoption. This finding suggests that the acceptance and integration of GenAI technologies are likely influenced by a broader and more complex array of organizational, cultural, and individual factors that were not captured in this study. Previous research has emphasized the potential roles of trust in AI systems (Gefen et al., 2003), perceived risk (Featherman & Pavlou, 2003), top management support (Ifinedo, 2011), organizational culture (Cameron, 2011), financial resources, and training availability as critical enablers or inhibitors of AI-related transformations. The absence of such variables in the present model may partly explain the modest variance explained and warrants further investigation. Perhaps even more striking is the finding that digital process usage—operationalized through the presence of tools such as ERP, CRM, RPA, and inventory tracking systems—did not have a statistically significant effect on any of the GenAI acceptance dimensions (performance expectancy, effort expectancy, facilitating conditions, or social influence). This challenges the commonly held assumption that digitally mature firms are inherently more prepared to integrate generative AI technologies. Instead, the findings indicate that mere digital tool adoption does not automatically translate into GenAI readiness. Several possible explanations can be considered in interpreting this outcome. First, the measurement method employed—counting the number of digital tools in use—may lack the sensitivity to capture meaningful differences in digital maturity or strategic alignment. Secondly, this research did not evaluate the depth or maturity of digital system implementation (for instance, the distinction between basic ERP usage and the integration of advanced analytics), which may conceal subtle variations in technological readiness. Moreover, the distinctive attributes of Generative AI—such as its cognitive, creative, and semi-autonomous capabilities—could present adoption challenges that diverge significantly from those experienced in traditional digitalization initiatives. Furthermore, the adoption of GenAI may be more significantly impacted by contextual hurdles like internal resistance to change, a lack of technical expertise, or ethical considerations than by the availability of digital processes alone. These revelations emphasize the significance of institutional, cultural, and human factors in assessing technology readiness and urge a reexamination of simplistic presumptions on digital transformation. To ensure a more complex, multifaceted view of AI adoption, future studies should look more closely at these factors. Although the adjusted R^2 values were relatively low, this outcome is not uncommon in social science research, particularly when studying complex organizational behaviors. The modest explanatory power indicates that additional contextual and organizational factors—such as leadership support, digital literacy, or cultural readiness—likely play a role in GenAI adoption. Importantly, the results still carry practical significance: the consistent positive effect of ChatGPT adoption across all GenAI dimensions highlights that even small but significant predictors can yield actionable insights for organizations. Thus, while the statistical models explain only a limited portion of variance, the findings remain relevant for managerial practice, especially in guiding digital transformation strategies and workforce training initiatives.

Within the context of the tested model, the rejection of hypotheses H1, H4, H7, and H10, alongside the finding that digital processes exert no statistically significant influence on factors associated with GenAI, stands out as one of the most noteworthy outcomes of this research. This finding shows that the presence of digital infrastructure or technological assets within the firms does not automatically lead to the adoption or effective use of the GenAI. It emphasizes that digital transformation extends beyond the acquisition of technologies and contains more complex dimensions such as effective use, organizational adaptation and cultural change. There are several possible reasons for these findings. First, in this study, the measurement of digital processes used a completely quantitative approach based on the number of digital technologies used and yes/no option. This approach could not achieve critical qualitative aspects such as digital maturity, depth of integration into basic business operations and general contribution of these technologies to performance results. Consequently, measurement may not fully reflect the real effectiveness or maturity of the digital capabilities of the companies. Another reason is that it does not mediate or control organizational factors that may affect the relationship between digital processes and geai adoption. These include management support, strategic vision, employee participation and training initiatives. For example, the lack of operating digital literacy or resistance to change may prevent the translation of digital infrastructure into GenAI adoption.

More thorough and multifaceted digital maturity models that incorporate both quantitative and qualitative markers, such as technology intensity, process alignment, user readiness, and strategy harmony, are advocated for use in future research. Research should also look into possible indirect routes, such as the function of organizational skills, worker satisfaction, or process optimization as a middleman. Conversely, barriers including employee reluctance, perceived risk, organizational inertia, and a lack of management support may limit the transformative potential of digital processes (Bharadwaj et al., 2013; Chen et al., 2014). Therefore, to accurately assess how digitization has shaped AI orbits, a more nuanced and integrative framework will be required. In the regression analysis, the use of digital technologies such as CRM, ERP, and Human Resources Software was coded as 'yes' 1 and 'no' 0. The results show that only the use of ChatGPT had a statistically significant and positive effect on all GenAI factors. This outcome highlights ChatGPT as the most prominent and impactful digital tool among those evaluated, as perceived by users. In contrast, other technologies—such as CRM, ERP, and human resources software—did not exhibit statistically significant effects ($p > 0.05$), suggesting that their influence on the dependent variables is negligible.

Similarly, AI applications used in companies have been evaluated solely based on their type and number of uses, without considering the frequency, level of integration, or success of these applications. Therefore, to more accurately analyze the impact of AI applications on performance, it is recommended that future studies collect data on usage intensity and perceived success.

Moreover, responses to the question "In which areas would you like to utilize AI?" were recorded numerically, without measuring the degree of desire (e.g., using a 5-point Likert scale). This approach provides limited insight into the nature of the demand for AI. Future studies would benefit from using scaled measurements that capture the intensity of participants' preferences, thus enabling a more nuanced understanding of companies' intentions regarding AI adoption.

The results reveal that while actual AI use has a large and positive impact on Effort Expectancy, Facilitating Conditions, and Social Influence, intention to use AI has a significant and positive impact on both Performance Expectancy and Social Influence. Hypotheses H2, H6, H9, H11, and H12 are so validated. These findings demonstrate how crucial user willingness and favorable opinions are in promoting the usage of generative artificial intelligence (GenAI). Perceived utility and preparedness to engage with a technology influence adoption behavior, according to existing research on technology acceptance frameworks (Venkatesh, Thong, & Xu, 2016). According to Williams, Rana, and Dwivedi (2015), social influence has a substantial predictive potential based on environmental forces and established norms.

Positive user attitudes and enthusiasm can hasten the adoption of new and difficult technologies, especially ones like artificial intelligence, according to recent research (Dwivedi et al., 2021). In this regard, businesses could adopt tactics to boost user motivation in addition to their technology investments. The establishment of peer support groups, awareness campaigns, and focused educational programs are a few examples of such actions.

Businesses should adopt a situation-specific approach to digital transformation and AI integration. AI literacy and human-centered design are crucial across all firm sizes (Lu, Papagiannidis, & Alamanos, 2021), but strategies should be tailored to industry and organizational capabilities. While large tech-focused companies invest heavily in AI and infrastructure, smaller firms may require training and change management for effective adoption (Kane et al., 2019). Collaborative human-machine interfaces can further enhance synergy between employees and intelligent systems (Shin, 2022).

The study also indicates that an organization's readiness to adopt GenAI is not strongly determined by existing digital processes. The low explanatory power of statistical models suggests that organizational, human, and contextual factors play a significant role in GenAI adoption, highlighting the need for a broader understanding of AI preparedness beyond digital infrastructure.

Recommendations for Future Research

Future studies should use more representative samples across industries and firm sizes, including SMEs and underrepresented sectors like manufacturing, retail, and healthcare, to better capture GenAI integration across digital maturity levels. Research should focus on the depth, integration, and effectiveness of digital technologies rather than tool counts, using digital maturity models to assess strategic alignment, data readiness, process automation, and innovation culture. Additional variables—such as trust in AI, perceived risk, top management support, organizational culture, digital literacy, regulatory environment, and resource availability—should be considered, as they may mediate or moderate GenAI adoption. Including demographic controls like gender, age, education, and job role could enhance analyses of individual attitudes and behavioral intentions. Longitudinal and qualitative approaches, including interviews and case studies, can better capture evolving adoption dynamics, organizational challenges, and employee interactions with GenAI, particularly in collaborative AI environments. Considering institutional, cultural, and technological factors would further improve model robustness and provide practical guidance for organizations.

Declarations

Funding: *No funding was received for conducting this study.*

Conflicts of Interest: *The author declares no conflict of interest.*

Ethical Approval: *This study was approved by the Istanbul Medipol University Social Sciences Ethics Committee (Approval date/number: 20.01.2025–17637).*

Informed Consent: *Informed consent was obtained from all participants prior to data collection. Participation was anonymous and limited to adults (18+), with confidentiality preserved throughout the study.*

Data Availability: *The datasets generated and analyzed during the current study are available from the corresponding author on reasonable request.*

AI Disclosure: *No artificial intelligence-based tools or applications were used in the preparation of this study. All content of the study was produced by the author in accordance with scientific research methods and academic ethical principles.*

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