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What Drives Artificial Intelligence Adoption Across Generations? The Influence of Trust, Literacy, and Perceived Usefulness

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Abstract

Artificial intelligence (AI) has become a central driver of technological, organizational, and social change. Despite its widespread diffusion, empirical evidence indicates that adoption patterns differ substantially across generational cohorts. This study examines how perceived usefulness, effort expectancy, digital literacy, social influence, and trust in privacy shape intentions to use AI technologies among Generation Z, Generation Y, and Generation X. Grounded in the Technology Acceptance Model (TAM) and its extensions, the study employs a quantitative survey design (N = 206) and applies correlational and multivariate regression analyses separately for each generational group. The findings demonstrate that effort expectancy is a robust predictor across all generations, while perceived usefulness, digital literacy, and social influence exert generationally differentiated effects. Contrary to common assumptions, trust in privacy does not significantly predict intention to use AI across cohorts. The study outcomes provide theoretical and practical implications for AI system design, education, and policy, emphasizing the importance of generationally tailored adoption strategies.

Keywords: List four to seven keywords separated with commas

INTRODUCTION

Over the past decade, artificial intelligence (AI) has emerged as a transformative technology shaping many aspects of everyday life. AI applications such as voice assistants (e.g., Siri, Alexa), recommendation systems (e.g., Netflix), and automated solutions in domains such as healthcare and education increasingly influence how people work, communicate, and learn. Beyond their technical capabilities, these technologies also raise important social and cultural questions related to technological accessibility, data privacy, and differences in adoption across demographic groups (Cheng & Lyu, 2024; Gerlich, 2023). Despite the growing prevalence of AI systems, their adoption is not uniform across user populations. In particular, generational differences appear to play a significant role in shaping attitudes toward emerging technologies. Younger cohorts, especially Generation Z and Generation Y, are generally characterized by higher levels of digital literacy and greater familiarity with technological innovations, which may facilitate the adoption of AI-based systems. In contrast, older cohorts, such as Generation X, may encounter greater barriers to adoption, including concerns about privacy, perceived system complexity, and lower levels of technological confidence (Shoukat et al., 2025). Understanding these differences is therefore essential for explaining the diffusion of AI technologies across society. A large body of research on technology adoption has drawn on the Technology Acceptance Model (TAM) and related frameworks to explain why individuals choose to adopt new technologies (Venkatesh et al., 2003). Within this literature, several key predictors have been consistently identified, including perceived usefulness, effort expectancy, social influence, and trust in data privacy (Ji et al., 2024). Perceived usefulness is often found to be one of the strongest drivers of adoption, as individuals are more likely to use technologies that improve efficiency or enhance performance (Na et al., 2022). Effort expectancy, which reflects the perceived ease of using a system, is a central construct in the Unified Theory of Acceptance and Use of Technology (UTAUT) and represents the degree to which individuals believe that interacting with a system requires minimal effort (Venkatesh et al., 2003, Emon et al., 2023). In addition, social influence, defined as the extent to which an individual's social environment affects their acceptance of artificial intelligence technology, can shape adoption decisions through peer norms and professional networks, especially among younger users (Hong, 2022). Trust in data privacy is another relevant factor, particularly for older users who may be more sensitive to concerns about protecting personal information (Shoukat et al., 2025).

Although these predictors have been widely examined in studies of technology acceptance, most prior research treats user populations as relatively homogeneous or focuses on a single demographic group. Consequently, less attention has been devoted to understanding how the relative importance of these predictors may differ across generational cohorts. In the context of rapidly evolving AI technologies, examining such generational differences may provide important insights into how technology acceptance processes vary across user groups. Against this background, the present study investigates how perceived usefulness, effort expectancy, social influence, digital literacy, and trust in data privacy influence intentions to use AI technologies among Generations Z and Y in comparison with Generation X. By examining these relationships across generational cohorts, the study aims to identify differences in the factors that drive AI adoption and to provide a more nuanced understanding of technology acceptance in contemporary digital environments. The findings of this study also highlight an unexpected empirical pattern: trust in data privacy does not significantly predict intention to use AI technologies across any of the examined generational cohorts. This result contrasts with prior research suggesting that privacy concerns often represent a major barrier to the adoption of digital technologies (Bélanger & Robert, 2024; Siau & Wang, 2020). One possible explanation for this pattern is the increasing normalization of privacy trade-offs in modern digital environments. As AI tools become embedded in widely used platforms and everyday applications, users may perceive the functional benefits of these technologies as outweighing potential privacy risks. Another possible explanation is privacy fatigue, in which individuals recognize privacy risks but continue to adopt digital technologies due to convenience, social norms, and perceived usefulness. These findings suggest that, in the context of widely accessible AI systems, usability and perceived value may play a more central role in adoption decisions than privacy considerations. This study contributes to the literature on technology acceptance and artificial intelligence adoption in several important ways. First, it extends the Technology Acceptance Model by examining generational heterogeneity in the determinants of AI adoption across Generations X, Y, and Z. While TAM has been widely used to explain technology adoption, relatively few studies have systematically compared predictor structures across generational cohorts within a single empirical framework. Second, the findings identify effort expectancy as the most consistent predictor of AI adoption intention across generations, highlighting the central importance of usability, simplicity, and cognitive accessibility in the design of AI systems. Third, the study demonstrates that trust in data privacy does not significantly predict AI adoption intention across generational cohorts, thereby challenging the common assumption that privacy concerns are a primary driver of technology adoption. By examining these relationships across generations, the present research provides new theoretical and empirical insights into the drivers of artificial intelligence adoption and offers practical implications for policymakers and technology developers seeking to promote inclusive and effective AI adoption.

From all of the above, the purpose of this research lies with the following **research question**:

***RQ**: What is the impact of perceived usefulness, trust in privacy, digital literacy effort expectancy and social influence on intention to use AI, and does this impact differ across Generations Z, Y, and X ?*

To answer this question, we formulated several hypotheses as shown below (The analysis of some of them will be shown in this conference paper):

H1: Perceived usefulness of AI is positively associated with intention to use AI, such that higher perceived usefulness is associated with stronger AI usage intentions.

H2: Trust in information privacy protection is positively associated with intention to use AI; in a way that higher levels of privacy trust will lead to stronger AI usage intentions.

H3: Digital literacy is positively associated with intention to use AI, such that higher levels of digital literacy are associated with stronger AI usage intentions.

H4: Effort expectancy is positively associated with intention to use AI in a way that higher effort expectancy (i.e., lower perceived effort) will lead to stronger AI usage intentions.

H5: Social influence is positively associated with intention to use artificial intelligence (AI) in a way that stronger social influence will be found as related to stronger AI usage intentions.

H6: Generational Moderation Hypothesis: Stronger associations between perceived usefulness and social influence and the intention to use AI are expected among younger generations (Generation Z and Generation Y), whereas stronger associations between trust in information (Data) privacy and effort expectancy and the intention to use AI, are expected among Generation X (see Table 1).

2. LITERATURE REVIEW

Since the early twentieth century, scholars and practitioners have envisioned technologies capable of understanding human language and enabling natural voice-based interaction (Na et al., 2022). In recent years, rapid technological advancement has accelerated the development of artificial intelligence (AI), positioning it as a transformative technology that enables real-time processing of complex data and conversational interfaces (Börekci & Çelik, 2024; Joaquim & Figueiredo, 2023; Vimalkumar et al., 2021). As a result, AI applications have been widely adopted across private and public sectors, including education, healthcare, engineering, and economics (Emon et al., 2023).

Voice-based assistants such as Alexa and Google Assistant exemplify the growing integration of AI into everyday life, supporting tasks such as scheduling, media consumption, and online purchasing (Na et al., 2022; Vimalkumar et al., 2021). AI systems are often described as "machines that display aspects of human intelligence" (Flavián et al., 2022, p. 4) and are widely associated with increased productivity, improved performance, and enhanced organizational competitiveness (Hong, 2022). At the same time, concerns persist regarding the potential displacement of human labor and the autonomous nature of AI-driven decision-making (Flavián et al., 2022; Hong, 2022).

Despite extensive research on AI adoption, limited attention has been paid to intergenerational differences and the combined effects of social influence, perceived usefulness, trust in data privacy, and digital literacy on intentions to use AI technologies among Generations X, Y, and Z. This gap is particularly salient given the evolving nature of human–machine interaction and the growing reliance on AI systems in professional and educational contexts (Roberts et al., 2025; Stolpe & Hallström, 2024).

Social influence has been consistently identified as a key determinant of AI adoption. Support from peers and the broader social environment increases acceptance of new technologies, as individuals tend to align their behavior with group norms and expectations (Emon et al., 2023; Na et al., 2022). Prior studies indicate that perceived social acceptance of AI use may even discourage non-adoption due to fears of social exclusion (Lin et al., 2020; Na et al., 2022).

Another central factor is perceived usefulness, defined as the extent to which individuals believe that using AI improves performance and efficiency (Börekci & Çelik, 2024; Na et al., 2022). Systems perceived as user-friendly and requiring minimal effort are more likely to be adopted, whereas complex or cognitively demanding systems reduce perceived usefulness and discourage use (Roberts et al., 2025). Accordingly, higher perceived usefulness is consistently associated with stronger intentions to adopt AI technologies (Hong, 2022).

Trust in data privacy represents an additional and often critical determinant of AI adoption. AI systems rely on extensive personal data, raising concerns about data storage, misuse, and security (Siau & Wang, 2020; Vimalkumar et al., 2021). Trust is therefore essential not only for task performance but also for confidence in responsible data management. Privacy concerns have been shown to exert a particularly strong influence on older users, who express heightened sensitivity to data protection risks (Shoukat et al., 2025).

Digital literacy has also become increasingly important in the context of AI adoption. Defined as the essential skills required for effective interaction with digital technologies (Börekci & Çelik, 2024), digital literacy enables individuals to search, evaluate, analyse, and apply digital information to generate new knowledge (Ji et al., 2024). Higher levels of digital literacy are associated with greater flexibility, problem-solving ability, and confidence in using advanced technologies, and are positively related to intentions to use AI systems (Emon et al., 2023; Vimalkumar et al., 2021).

The literature further highlights that AI adoption intentions vary significantly across populations and contexts. Studies conducted in rural communities, national populations, and organizational settings consistently demonstrate that perceived usefulness, social influence, effort expectancy, digital literacy, and trust-related factors shape AI adoption, albeit with varying relative importance (Emon et al., 2023; Ji et al., 2024; Shoukat et al., 2025).

These variations are closely linked to generational differences, which emerge from shared historical experiences, technological exposure, and value systems (Mahmoud et al., 2021). Contemporary workplaces increasingly comprise employees from Generations X, Y, and Z, whose differing levels of digital skills, communication preferences, and attitudes toward technology may lead to divergent perceptions of AI. While older generations may perceive AI as a threat to job security due to lower digital competence, younger generations tend to favor rapid, informal, and technology-mediated communication and demonstrate greater openness to AI adoption (Joaquim & Figueiredo, 2023; Mahmoud et al., 2021).

Taken together, the literature underscores the need for integrative research that systematically examines how perceived usefulness, social influence, digital literacy, cognitive demands, and trust in privacy interact across generations to shape intentions to use AI technologies. Addressing this gap is essential for designing inclusive, effective, and socially responsible AI systems.

3. RESEARCH METHODOLOGY

3.1 Study Design

This study employed a quantitative, cross-sectional research design to examine the determinants of intention to use artificial intelligence (AI) technologies. Specifically, it investigated the relationships between perceived usefulness, trust in data privacy, social influence, effort expectancy, and digital literacy, and their impact on individuals' intention to use AI. In addition, the study explored whether these relationships differ across generational cohorts, Generation X, Generation Y, and Generation Z. The chosen design is appropriate for testing theory-driven associations among latent constructions and for identifying age-related differences in technology adoption patterns.

3.2 Research Hypotheses

The research hypotheses posit positive relationships between the proposed independent variables and individuals' intention to use artificial intelligence (AI). Specifically, social influence (H1), perceived usefulness (H2), trust in data privacy (H3), effort expectancy (H4), and digital literacy (H5) are each hypothesized to have a positive effect on intention to use AI. In addition, the generational cohort is examined as a grouping variable to explore potential differences in the relative importance of AI adoption predictors across Generations X, Y, and Z (Table 1).

3.3 Participants and Sampling

The study sample consisted of approximately 200 participants aged 18 to 65, representing three generational cohorts based on established classifications (Joaquim & Figueiredo, 2023): Generation Z (18–26 years), Generation Y (27–42 years), and Generation X (43–65 years). Participants were recruited using a non-probabilistic snowball sampling technique, whereby initial respondents were asked to distribute the questionnaire to peers and acquaintances. This approach enabled access to a heterogeneous sample across age groups, although it may limit generalizability due to potential self-selection bias.

Participation was voluntary and anonymous. Respondents provided only basic demographic information, including age, gender, and educational level. Other demographic variables, such as marital status, religion, ethnicity, and income, were not collected and therefore could not be controlled for in the analysis.

3.4 Research Instruments

The study employed previously validated measurement scales adapted from prior research.

Social influence was measured using a five-item scale assessing the extent to which individuals perceive that important others believe they should use a particular technology (Venkatesh et al., 2003). The scale demonstrated acceptable reliability (Cronbach's $\alpha = .74$).

Perceived usefulness, defined as the degree to which participants believe that artificial intelligence (AI) technologies enhance their performance and efficiency, was measured using a five-item scale adapted from Davis (1989). The scale exhibited excellent internal consistency (Cronbach's $\alpha = .94$).

Trust in data privacy, reflecting participants' confidence in AI systems' ability to protect personal information, was assessed using a five-item scale adapted from Malhotra et al. (2004). The scale's reliability was satisfactory (Cronbach's $\alpha = .77$).

Effort expectancy, capturing the perceived ease of use and the mental effort required to operate AI systems, was measured using a six-item scale derived from Venkatesh et al. (2003). The scale demonstrated high reliability (Cronbach's $\alpha = .93$). Reverse-coded items were recoded prior to analysis so that higher values indicated greater perceived ease of use.

The above constructs were measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Composite scores for each construct were calculated by averaging the responses across the corresponding items.

Digital literacy was measured using a three-item scale assessing participants' self-reported technical skills and their ability to interact effectively with digital technologies (Van Deursen & Van Dijk, 2014). The scale demonstrated good reliability (Cronbach's $\alpha = .81$).

The dependent variable, *intention to use AI*, was measured using a four-item scale capturing participants' willingness to adopt and use AI technologies in practice (Davis, 1989). The scale demonstrated good internal consistency (Cronbach's $\alpha = .81$).

Across all constructs, composite scores were computed by averaging the relevant item responses prior to statistical analysis.

3.5 Procedure

The questionnaire was distributed exclusively in digital form via social media platforms such as Facebook and WhatsApp, as well as through direct email invitations. Participants were informed about the purpose of the study and provided informed consent prior to participation. The questionnaire required approximately 10 minutes to complete. No personally identifiable information was collected.

3.6 Data Analysis

Data was analyzed using IBM SPSS Statistics. The analysis included descriptive statistics to summarize participant characteristics and key variables, followed by inferential analyses to test and validate the research hypotheses, as per the literature (Zwilling et al., 2022).

Because the study's hypotheses predicted directional relationships between the independent variables and intention to use AI, one-tailed tests were used in the correlation analyses.

Pearson correlation analyses were conducted to examine relationships between variables. Group differences across generational cohorts were examined using independent-samples t-tests and analysis of variance (ANOVA). Multiple linear regression analysis was also performed to identify predictors of intention to use AI and to assess the relative contribution of each independent variable.

In the regression model for Generation Y, one predictor variable was excluded during model estimation due to statistical redundancy and lack of additional explanatory contribution, resulting in a slightly different number of predictors compared with the other cohort models. Additional analyses examined the potential effects of gender and education level when relevant.

3.7 Research Model

This study proposes a research model in which intention to use AI technologies is explained by social influence, perceived usefulness, trust in data privacy, effort expectancy, and digital literacy. All constructs are hypothesized to have direct positive effects on AI usage intention. In addition, generational cohort (Generation Z, Y, and X) is examined as a grouping factor used to compare the relative strength of the predictors across generational cohorts. across age groups (Figure 1).

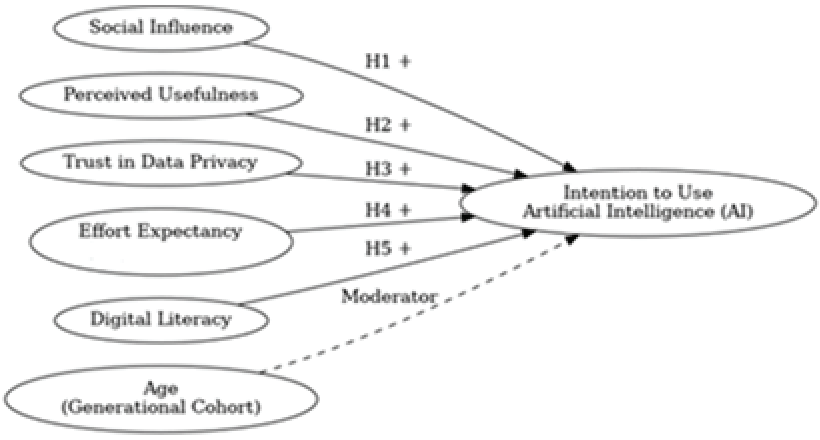

Figure 1. Proposed Research Model of AI Usage Intention Across Generational Cohorts

Table 1. Summary of Research Hypotheses and Expected Effects on Intention to Use AI

Hypothesis	Independent Variable	Dependent Variable	Expected Direction
H1	Social Influence	Intention to Use AI	Positive (+)
H2	Perceived Usefulness	Intention to Use AI	Positive (+)
H3	Trust in Data Privacy	Intention to Use AI	Positive (+)
H4	Effort Expectancy	Intention to Use AI	Positive (+)
H5	Digital Literacy	Intention to Use AI	Positive (+)
H6	Age (Generational Cohort)	Comparison across cohorts	Cohort-based differences

4. FINDINGS

4.1 Sample characteristics and descriptive profile

The study sample comprised 206 participants distributed across three generational cohorts: **Generation Z** (ages 18–26; n = 57, 27.67%), **Generation Y** (ages 27–42; n = 58, 28.16%), and **Generation X** (ages 43–65; n = 91, 44.17%). Accordingly, the sample provides substantial representation of both younger cohorts (55.82% aged 18–42) and older participants, with Generation X constituting the largest group.

Overall, the gender composition of the sample was 40.78% men (n = 84) and 59.22% women (n = 122). Gender distribution varies across generational cohorts. Generation Z included a higher proportion of men (59.65%) than women (40.35%), Generation Y exhibited an approximately balanced gender distribution, and Generation X was predominantly female (75.82%). Given this uneven gender distribution across cohorts, interpretations of generational differences were approached with appropriate caution.

Figure 2 illustrates the generational distribution of the sample, while Figure 3 depicts gender composition within each generational cohort.

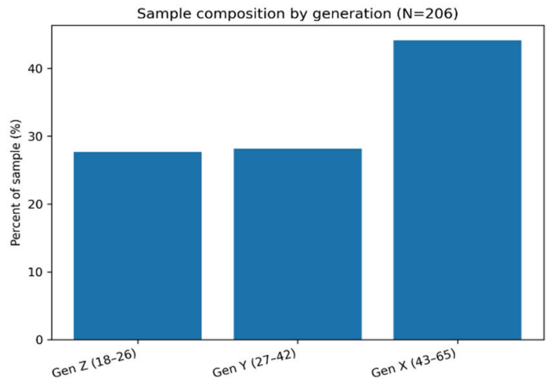

Figure 2: Sample Composition by Generation (N = 206)

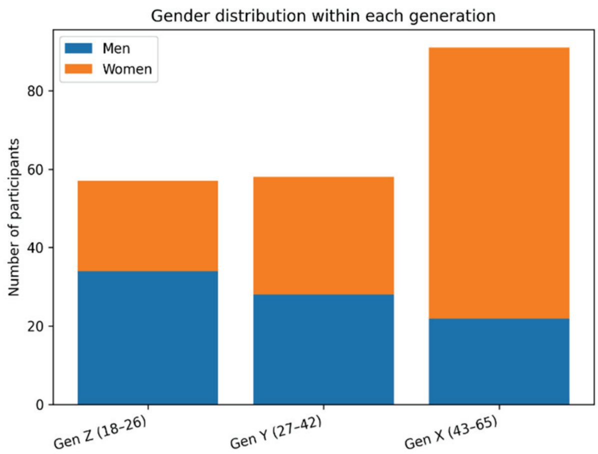

Figure 3. Gender Distribution Across Generational Cohorts

4.2 Descriptive Statistics

The means (M) and standard deviations (SD) of the study variables across the three generational cohorts was analyzed as shown in Table 2 (Table 2). Overall, the descriptive findings indicate moderate to relatively high mean values for social influence and perceived usefulness across all generations, reflecting a generally favorable orientation toward AI technologies. Digital literacy yielded the highest mean scores, particularly among Generation Z and Generation Y, suggesting higher levels of self-perceived technological proficiency within younger cohorts. Conversely, trust in data privacy exhibited comparatively lower mean levels among Generations Z and Y, whereas Generation X reported moderately higher levels of privacy trust. Effort expectancy displayed lower mean values across cohorts, with Generation Y indicating the lowest perceived effort associated with AI use. It should be noted that because several items measuring effort expectancy were reverse-coded, lower mean values indicate greater perceived ease of use rather than lower perceived importance of the construct. Taken together, these descriptive patterns reveal meaningful generational differences in baseline perceptions related to AI adoption. These observed differences provide an empirical basis for subsequent correlation and regression analyses that examine the strength and direction of relationships between these variables and intention to use AI across generational groups.

Table 2: Descriptive Statistics of the Study Data

Variable	Age Group	Mean (M)	Standard Deviation (SD)	N
Social Influence	Generation Z (18–26)	3.40	1.178	57
	Generation Y (27–42)	3.48	1.287	58
	Generation X (43–65)	3.44	1.213	91
Perceived Usefulness	Generation Z (18–26)	3.74	1.302	57
	Generation Y (27–42)	3.72	1.424	58
	Generation X (43–65)	3.58	1.274	91
Trust in Data Privacy	Generation Z (18–26)	2.49	1.197	57
	Generation Y (27–42)	2.52	1.246	58
	Generation X (43–65)	3.02	1.410	91
Effort Expectancy	Generation Z (18–26)	2.05	1.301	57
	Generation Y (27–42)	1.72	0.969	58
	Generation X (43–65)	1.82	1.101	91
Digital Literacy	Generation Z (18–26)	4.09	1.010	57
	Generation Y (27–42)	3.93	0.970	58
	Generation X (43–65)	3.46	1.220	91

4.3 Bivariate Associations Between Predictors and Intention to Use AI

To test the study hypotheses, the sample was stratified into three age cohorts (Generation Z, Generation Y, and Generation X), and each hypothesized relationship was examined separately within each cohort using Pearson's product–moment correlations (one-tailed). Overall, the correlation patterns were highly consistent across cohorts: **social influence, perceived usefulness, effort expectancy, and digital literacy were positively associated with AI use intention**, whereas **privacy trust was not significantly associated with intention in any cohort**. Specifically, **H1** (Social Influence → AI Intention) was supported in all cohorts (Gen Z: $r = .462$, $p < .001$; Gen Y: $r = .655$, $p < .001$; Gen X: $r = .550$, $p < .001$). **H2** (Perceived Usefulness → AI Intention) was also supported across cohorts (Gen Z: $r = .556$, $p < .001$; Gen Y: $r = .703$, $p < .001$; Gen X: $r = .667$, $p < .001$). **H3** (Privacy Trust → AI Intention) was not supported, with weak and nonsignificant correlations (Gen Z: $r = -.058$, $p = .333$; Gen Y: $r = -.065$, $p = .315$; Gen X: $r = .035$, $p = .372$). **H4** (Effort Expectancy → AI Intention) was strongly supported and yielded the largest association in each cohort (Gen Z: $r = .625$, $p < .001$; Gen Y: $r = .769$, $p < .001$; Gen X: $r = .600$, $p < .001$). Finally, **H5** (Digital Literacy → AI Intention) was supported across cohorts (Gen Z: $r = .511$, $p < .001$; Gen Y: $r = .434$, $p < .001$; Gen X: $r = .464$, $p < .001$). Taken together, these findings suggest that across generations, AI adoption intention is principally explained by performance- and usability-related beliefs (usefulness and ease of use), complemented by social and capability-related factors (social influence and digital literacy), while privacy-related trust does not appear to function as a bivariate driver of intention in this dataset. The Hypothesis Testing Summary is presented in Table 3.

Table3. Hypothesis Testing Summary: Pearson Correlations Between Predictors and Intention to Use AI by Age Cohort (One-Tailed Tests)

Hypothesis	**Predictor → Outcome**	**Generation Z (*N* = 57)**	**Generation Y (*N* = 58)**	**Generation X (*N* = 91)**	**Outcome (Confirmed)?**
H1	Social influence → AI intention	r = .462, p < .001	r = .655, p < .001	r = .550, p < .001	Yes (all)
H2	Perceived usefulness → AI intention	r = .556, p < .001	r = .703, p < .001	r = .667, p < .001	Yes (all)
H3	Privacy trust → AI intention	r = −.058, p = .333	r = −.065, p = .315	r = .035, p = .372	No (all)
H4	Effort expectancy → AI intention	r = .625, p < .001	r = .769, p < .001	r = .600, p < .001	Yes (all)
H5	Digital literacy → AI intention	r = .511, p < .001	r = .434, p < .001	r = .464, p < .001	Yes (all)

While the correlation analysis provides initial evidence of relationships between the predictors and AI adoption intention, multiple regression analyses were conducted to examine the relative contribution of each predictor while controlling for the others.

4.4 Familiarity with AI tools

Across all cohorts, ChatGPT was the most familiar tool. Mean familiarity with ChatGPT was highest in Generation Z (M = 4.32, SD = 0.985), followed by Generation Y (M = 4.14, SD = 1.067), and Generation X (M = 3.71, SD = 1.176). Familiarity with Gemini and Claude was lower across all cohorts and lowest among Generation X, consistent with a cohort-based gap in exposure to newer AI platforms (Figure 4)

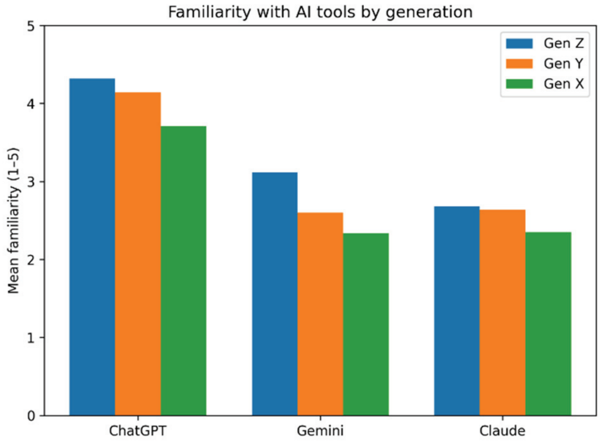

Figure 4: Familiarity with AI Tools by Generational Cohort

4.5 Means of intention to use and predictors by generation

Intention to use AI was high across all cohorts: Generation Z (M = 4.07, SD = 1.178), Generation Y (M = 4.05, SD = 1.190), and Generation X (M = 3.89, SD = 1.178). Although Generation X reported slightly lower intention, the mean remains high, indicating broad acceptance rather than resistance (Figure 5).

Predictor means suggest meaningful cohort patterns: digital literacy was highest in Generation Z (M = 4.09) and lowest in Generation X (M = 3.46), whereas privacy trust was highest in Generation X (M = 3.02) compared to Generations Z and Y (≈2.5). Effort expectancy (perceived ease/low cognitive burden) was lowest in Generation Y (M = 1.72) relative to Z (M = 2.05) and X (M = 1.82), indicating cohort variation in perceived "effort" associated with AI use (Figure 6).

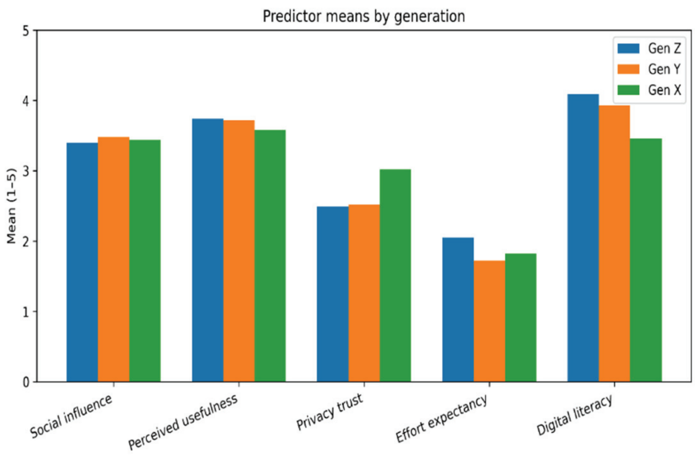

Figure 5. Mean Values of AI Adoption Predictors by Generational Cohort

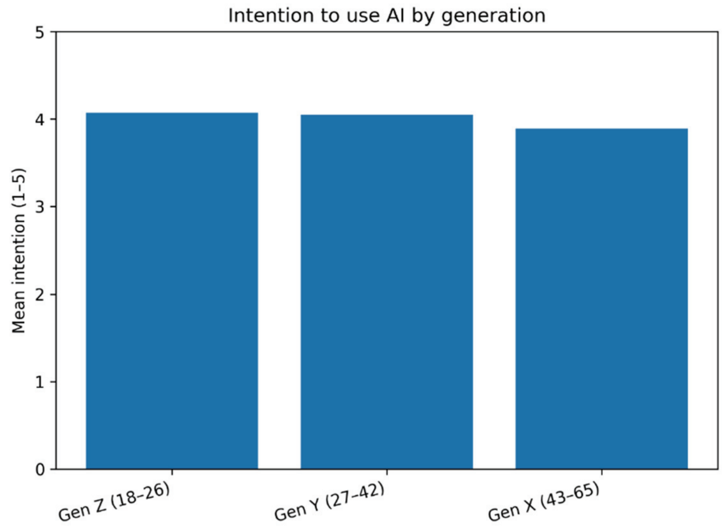

Figure 6. Intention to Use Artificial Intelligence by Generational Cohort

4.7 Regression Analyses by Generation

Prior to conducting the regression analyses, multicollinearity diagnostics were examined. Variance Inflation Factor (VIF) values ranged between 1.21 and 2.34, indicating that multicollinearity was not a concern in the regression models (Low correlation).

To test the research hypotheses in a multivariate context, separate multiple linear regression models were estimated for each generational cohort, predicting intention to use artificial intelligence (AI) from social influence, perceived usefulness, trust in data privacy, effort expectancy, and digital literacy. All models demonstrated strong explanatory power, although the pattern of significant predictors differed across cohorts. For Generation Z, the regression model explained a substantial proportion of variance in intention to use AI ($R^2 = .504$, $F(5, 51) = 10.371$, $p < .001$). Within this cohort, effort expectancy emerged as the only significant predictor ($\beta = .315$, $p = .037$), indicating that perceived ease of use and cognitive effort play a central role in AI adoption among younger users. Perceived usefulness approached statistical significance ($\beta = .247$, $p = .063$), whereas social influence, digital literacy, and trust in data privacy were not significant predictors (all *ps* > .20). For Generation Y, the model demonstrated very strong explanatory power, accounting for 74.2% of the variance in intention to use AI ($R^2 = .742$, $F(4, 53) = 38.024$, $p < .001$). In this cohort, effort expectancy was the strongest predictor ($\beta = .594$, $p < .001$), followed by perceived usefulness ($\beta = .365$, $p = .001$) and digital literacy ($\beta = .290$, $p = .005$). Social influence and trust in data privacy did not significantly contribute to the model (all *ps* > .27). For Generation X, the regression model also showed a strong fit ($R^2 = .592$, $F(5, 85) = 24.713$, $p < .001$). In contrast to younger cohorts, perceived usefulness emerged as the strongest predictor of intention to use AI ($\beta = .425$, $p < .001$), followed by effort expectancy ($\beta = .355$, $p = .001$). Additionally, social influence was a significant predictor in this cohort ($\beta = .189$, $p = .029$), suggesting greater sensitivity to normative and social factors among older users. Digital literacy and trust in data privacy were not significant predictors (all *ps* ≥ .86).

Overall, the regression findings indicate that effort expectancy is a consistent and robust predictor of intention to use AI across generations, while perceived usefulness is particularly influential for

Generations Y and X. Social influence contributes uniquely to AI adoption among Generation X, whereas digital literacy is significant only for Generation Y. Notably, trust in data privacy does not significantly predict intention to use AI in any generational cohort. Figure 7 presents the standardized regression coefficients, visually highlighting differences in predictor importance across generations. In addition, Figure 8 presents a heatmap of standardized regression coefficients (β) across generational cohorts, offering a compact visualization of the relative importance of each predictor of intention to use AI. The heatmap highlights clear generational differences: effort expectancy emerges as the strongest predictor for Generations Z and Y, whereas perceived usefulness is most influential for Generation X. Digital literacy shows a meaningful contribution primarily for Generation Y, while social influence is comparatively more salient for Generation X. In contrast, trust in data privacy exhibits minimal and inconsistent effects across cohorts. Overall, the heatmap complements the regression results by emphasizing cross-generational contrasts in predictor strength and direction. In addition, relative importance of predictors of AI adoption across generations is shown in Figure 9.

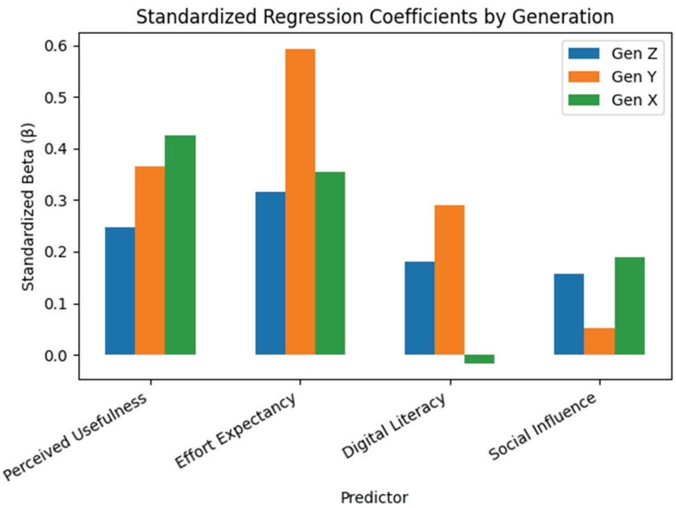

Figure 7. Standardized Regression Coefficients Predicting Intention to Use AI by Generational Cohort

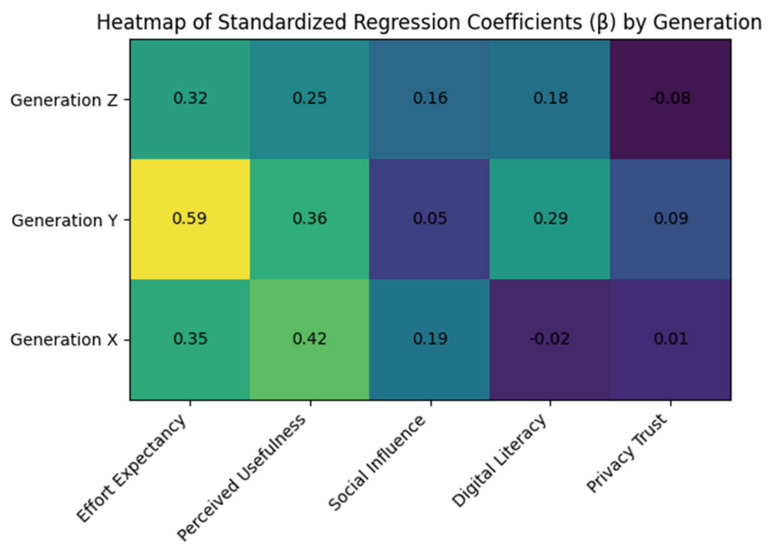

Figure 8. Heatmap of Standardized Regression Coefficients (β) by Generational Cohort

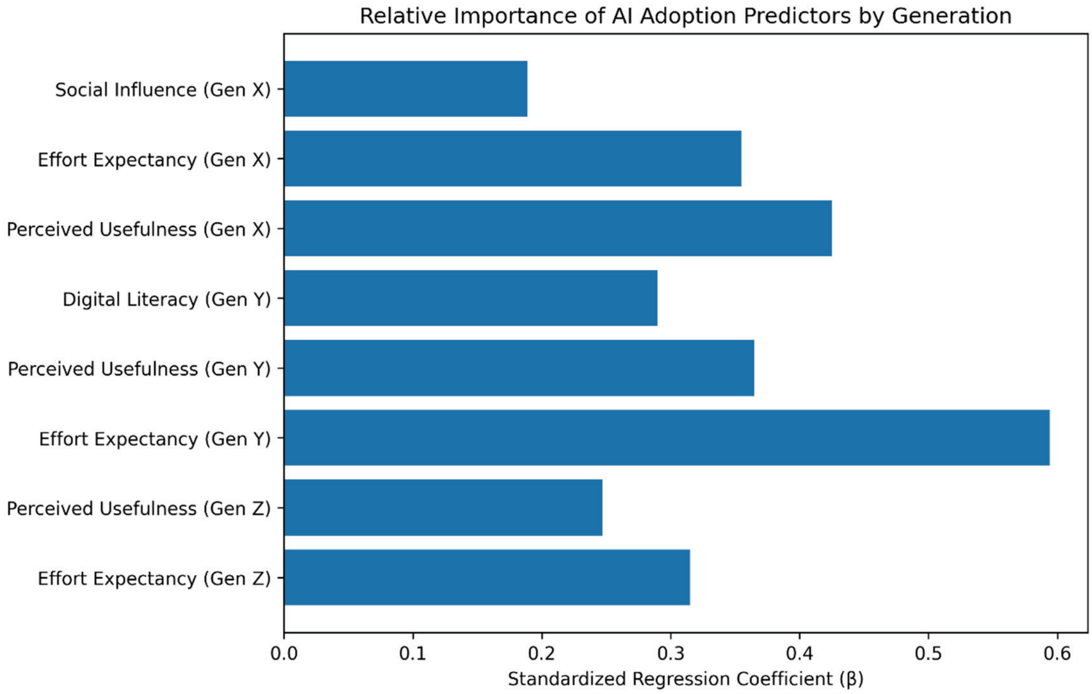

Figure 9: Relative importance of predictors of AI adoption across generations. The figure presents standardized regression coefficients (β) illustrating the relative importance of predictors of AI adoption intention across generational cohorts.

5. DISCUSSION

From a theoretical perspective, the present study contributes to the literature on technology acceptance and artificial intelligence adoption by highlighting the importance of generational differences in evaluating AI technologies. The findings demonstrate that while several determinants of technology acceptance remain relevant across cohorts, their relative importance varies between generations. In particular, the consistent influence of effort expectancy across cohorts emphasizes the importance of usability-oriented design principles in AI systems. At the same time, the non-significant role of privacy trust suggests that traditional concerns regarding privacy risks may play a less central role in AI adoption decisions than previously assumed. These findings contribute to a more nuanced understanding of AI adoption by demonstrating that generational context can influence how users evaluate both the benefits and the perceived risks of emerging technologies.

Overall, the findings of the present study demonstrate that intention to use artificial intelligence (AI) technologies is shaped by a combination of technological, perceptual, and social factors, but not uniformly across age groups. Clear generational differences emerged, indicating that users at different life stages rely on distinct motivations and evaluative criteria when considering AI adoption. Among the five examined predictors, perceived usefulness, effort expectancy, digital literacy, trust in data privacy, and social influence, only effort expectancy and perceived usefulness showed consistent relevance across cohorts.

For **Generation Z (ages 18–26)**, effort expectancy was the strongest and only significant predictor of intention to use AI, while perceived usefulness approached significance. This suggests that younger users primarily evaluate AI technologies based on ease of use and user experience rather than functional value or social considerations. These results align with prior research indicating that younger cohorts are more likely to adopt innovations perceived as intuitive and frictionless.

In contrast, **Generation Y (ages 27–42)** exhibited the most robust explanatory model, accounting for over 74% of the variance in intention to use AI. In this cohort, effort expectancy, perceived usefulness, and digital literacy were all significant predictors. This pattern indicates that Generation Y combines functional efficiency with technological confidence and personal competence when evaluating AI. Digital literacy emerged as a key enabling factor, facilitating users' ability to recognize benefits and overcome usage barriers, positioning this group as a strategic target for AI implementation initiatives.

Among **Generation X (ages 43–65)**, intention to use AI was primarily driven by perceived usefulness and effort expectancy, with social influence also playing a significant role. This suggests that older users approach AI adoption as a rational, value-based decision, while remaining sensitive to social norms and environmental cues. Contrary to common assumptions, trust in data privacy was not a significant predictor in this cohort, possibly reflecting a normalization of privacy trade-offs in the digital age, as long as perceived benefits outweigh potential risks.

Across all cohorts, effort expectancy emerged as the only universally significant predictor, underscoring the central importance of usability and intuitive design in AI systems. Simplicity, accessibility, and low cognitive burden appear critical for widespread adoption. Perceived usefulness was especially influential among older users, highlighting the importance of clearly communicated, tangible value.

Overall, the findings suggest that AI adoption is a multidimensional and age-dependent process. Generation Z is primarily motivated by usability, Generation Y by a combination of usability, usefulness, and digital competence, and Generation X by practical value and social context. These differences underscore the need for age-sensitive design, communication, and implementation strategies to reduce digital gaps and promote informed, equitable AI use.

6. Practical Implications

The results highlight the importance of tailoring AI systems to the psycho-social characteristics of different age groups. For younger users, emphasis should be placed on streamlined interfaces and intuitive interaction. For middle-aged users, enhancing transparency, control, and technological self-efficacy is essential. For older users, demonstrating concrete benefits and reinforcing social legitimacy may be most effective. A generationally adaptive approach may enhance accessibility, foster trust, and increase overall acceptance of AI technologies.

7. Limitations and Future Research

Several limitations should be considered when interpreting these findings. First, the use of snowball sampling may limit representativeness and introduce selection bias toward technologically engaged participants. Second, reliance on self-reported data may not fully reflect actual behavior. Third, the sample also included participants with relatively high digital literacy, potentially constraining generalizability to less digitally skilled populations. Additionally, statistical constraints prevented formal between-group comparisons of effect sizes. The non-significant role of privacy trust may reflect measurement limitations or insufficient scale sensitivity. Finally, generational patterns were explored through cohort-specific regression analyses, which allow for descriptive comparisons across groups.

However, the study did not formally test moderation effects using interaction terms or multi-group structural equation modelling. Future research may employ such analytical techniques to more rigorously examine whether generational membership moderates the relationships between key predictors and AI adoption intentions.

Future research should extend this work by including additional age cohorts, such as Generation Alpha and Baby Boomers, and by examining cross-cultural contexts where privacy norms and perceptions of technology differ. A mixed methods approach, including qualitative interviews or focus groups, could provide deeper insight into underlying motivations. Further studies should also explore occupational differences and evaluate targeted digital literacy interventions to assess their impact on perceived usefulness and AI adoption intentions.

In addition, the study did not formally test moderation effects using interaction terms or multi-group structural equation modeling. Instead, generational differences were explored through cohort-based regression analyses. Future studies may employ more advanced analytical techniques to formally examine moderation effects.

Future research could also further explore the unexpectedly high participation of Generation X in the study. Additional research may examine why individuals from this generation appear willing to engage with discussions about AI and digital technologies, and whether this reflects a growing awareness of the human and societal challenges associated with AI. In addition, future studies may investigate gender differences in social media engagement within Generation X, including why women in this cohort appear particularly active. Examining whether these patterns are related to motivational factors, technological engagement, or the method of survey distribution may provide valuable insights.

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