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Prior AI Experience and Attitude toward Generative AI Tools among Low-Income Individuals in South Korea: A Serial Mediation Model

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ABSTRACT

Focusing on the generative artificial intelligence (AI) tools using large language models, the present research explores the individual factors impacting the low-income Koreans' attitudes toward generative AI tools utilized to search for information (e.g., ChatGPT, Google Gemini, etc.). Specifically, we first examine whether low-income Korean individuals' prior AI experience, perceived usefulness of AI, and general attitude toward AI influence their attitudes toward generative AI tools (RQ1). Second, we examine whether the prior AI experience affects the attitude toward generative AI tools via the perceived usefulness of AI (RQ2). Third, we examine whether the prior AI experience influences the attitude toward generative AI tools via the general attitude toward AI (RQ3). Fourth, we examine whether the relationship between prior AI experience and attitude toward generative AI tools is serially mediated by the perceived usefulness of AI and general attitude toward AI (RQ4). To answer the research questions, we conducted a hierarchical multiple regression analysis and a mediation analysis using the low-income Koreans who were aware of the generative AI tools (n = 770). The results indicate that (1) both the perceived usefulness of AI and general attitude toward AI are positively associated with the attitude toward generative AI tools; (2) the perceived usefulness of AI mediates the relationship between the prior AI experience and the attitude toward generative AI tools; (3) the indirect effect of prior AI experience on the attitude toward generative AI tools, via the general attitude toward AI, is not statistically significant; and (4) the prior AI experience influences the attitude toward generative AI tools through a sequential process of the perceived usefulness of AI and general attitude toward AI. The findings provide important implications to enhance the attitude toward generative AI tools.

Keywords: Artificial Intelligence (AI), Generative AI, Experience, Perceived Usefulness, Attitude.

INTRODUCTION

Recently, there has been significant attention on the progress of artificial intelligence (AI), particularly with the advent and swift evolution of publicly accessible AI tools. AI-based applications have revolutionized the way people think, behave and live in this post-pandemic era, performing a wide range of tasks, from simple manual labor to complex operations. At the heart of this shift is the concept of "generative AI," a forefront area in machine learning technologies noted for its exceptional ability to generate new content [1]. Generative AI represents a new generation of AI technologies that produce new digital content based on user-inserted prompts [2]. Via generative AI, users can simply tell the AI tool the type and nature of the outputs they want, and the AI will generate the requested outputs. For instance, generative AI applications include Chat Generative Pre-trained Transformer (ChatGPT) and Google Gemini (formerly Bard) for writing texts, Dall-E and Midjourney for creating realistic images and visual art, Steve AI for producing videos and animations, and Boomy for making original music.

The evolution of AI has witnessed a crucial turn with the advent of large language models (LLMs) that generate human-like responses from inputs, or prompts, through natural language processing (NLP) and statistics [3]. When it comes to searching for information, in particular, AI-powered chatbots such as ChatGPT and Google Gemini apply

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generative AI techniques to provide algorithm-generated conversational responses to question prompts [4]. That is, such generative AI tools as ChatGPT and Google Gemini provide immediate answers and responses to almost all questions users ask for, like Google and Yahoo search engines. ChatGPT developed by OpenAI is a large multimodal model (LMM) which was trained on both text and pixel features (from images), while Google Gemini is an LLM that uses Google Lens for text recognition.

Both ChatGPT and Google Gemini have recently increased the power of consumer marketing and the effectiveness of customer service [5-7]. They offer useful services and are utilized in a variety of fields such as education, information retrieval, business, and e-commerce [8]. The potential applications of AI tools herald a new age for the marketing and advertising sectors, offering unprecedented opportunities for growth and optimization [7]. For example, the potential of generative AI will inspire ad creation through compelling brand stories, preventing stereotypes, and providing innovative solutions to marketing problems. In addition, by understanding consumer emotions and motivations, marketers will be able to create campaigns that resonate with actual consumer needs and motivations. Most importantly, generative AI technology will enable businesses to better empathize with their clients and understand changes in consumer behavior, in order to make substantial and informed decisions [7].

In this regard, this research primarily focuses on the generative AI tools utilized to search for information (e.g., ChatGPT, Google Gemini, etc.). Moreover, in spite of the potentially significant role of AI in various domains, a major drawback of the predominant studies is that AI and its development are centered on the needs, necessities, and values of the high-income countries, which are at the forefront of AI advancement [9, 10]. Therefore, we explore the individual factors impacting the low-income Korean individuals' attitudes toward generative AI tools. Specifically, we first examine whether low-income Koreans' prior experience in using AI-based services (i.e., prior AI experience), perceived usefulness of AI, and general attitude toward AI influence their attitudes toward generative AI tools. Second, we examine whether the prior AI experience affects the attitude toward generative AI tools via the perceived usefulness of AI. Third, we examine whether the prior AI experience influences the attitude toward generative AI tools via the general attitude toward AI. Fourth, we examine whether the relationship between prior AI experience and attitude toward generative AI tools is serially mediated by the perceived usefulness of AI and general attitude toward AI.

LITERATURE REVIEW AND RESEARCH QUESTIONS

Experience has been found to be a crucial determinant of behavior [11]. In the case of information communication technology (ICT) usage, experience is significant because prior experience allows users to better perceive low probability events, ensuring that they will account for them in the formation of intentions [12]. Besides, it has been observed that people can use ICT systems more adeptly through knowledge and confidence gained from direct experience [13]. Prior studies have revealed that experience is a major factor in the formation of intentions to use systems [14], and the quantity of experience is positively associated with an individual's perception that the system is easy to use [15].

Perceived usefulness of AI refers to the extent to which a user believes that AI will enhance their job performance or productivity. The positive impact of perceived benefits on individuals' decision-making process and purchase outcomes has been supported by a large body of research in the context of marketing and social media [16]. Users are more likely to accept and adopt new technology if they perceive it as beneficial in achieving their goals or tasks [17]. The perceived usefulness of AI is intricately linked to an individual's motivation to use AI. If individuals perceive AI as useful, they are more likely to be motivated to use it [18]. Conversely, if AI is perceived as not useful, their motivation to use it diminishes. In the technology acceptance model (TAM), perceived usefulness is a crucial factor influencing an individual's attitude and intention toward technology usage [19]. The model suggests that individuals are more inclined to adopt and utilize technology if they believe it aids in accomplishing their goals and tasks [20].

General attitude toward AI refers to the user's general positive or negative evaluation of AI [21]. In the TAM, attitude is seen as a reflection of an individual's subjective evaluation of a technology based on its perceived usefulness and ease of use [22-25]. Hence, if individuals perceive AI to be useful and easy to use, they are likely to have a positive attitude toward AI, which increases their intention to use it [26]. Conversely, if individuals perceive AI to be not

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useful or difficult to use, they are likely to have a negative attitude towards AI, which decreases their intention to use it [27].

It has recently been suggested in the consumer research literature that consumer attitudes are inherently bidimensional because consumers purchase products/services and perform consumption behaviors for two basic reasons: instrumental/utilitarian vs. affective/hedonic reasons [28]. In a similar vein, the distinction between instrumental/cognitive versus experiential/affective components of attitudes is long established [29]. The cognitive component of attitude (or cognitive attitude) is considered to be the evaluation implied by cognition about an attitude object [30], while the affective component of attitude (or affective attitude) is considered to be the evaluation implied by feelings (or emotions) about an attitude object [31]. Thus, in the context of generative AI tools, cognitive attitudes reflect consumers' assessment of how beneficial or useful buying them. As noted, in the TAM, attitude is seen as a reflection of an individual's subjective evaluation of a technology based on its perceived usefulness and ease of use [25, 32]. Hence, if individuals perceive AI to be beneficial, they are likely to have a positive attitude toward AI-based products or services, which in turn increases their intention to use them [26].

Drawing on the previous findings, therefore, we first examine whether low-income Korean individuals' prior AI experience, perceived usefulness of AI, and general attitude toward AI influence their attitudes toward generative AI tools, controlling for the effects of demographic variables and prior usage experience with generative AI tools (RQ1). Second, we examine whether the prior AI experience affects the attitude toward generative AI tools via the perceived usefulness of AI (RQ2). Third, we examine whether the prior AI experience influences the attitude toward generative AI tools via the general attitude toward AI (RQ3). Fourth, we examine whether the relationship between prior AI experience and attitude toward generative AI tools is serially mediated by the perceived usefulness of AI and general attitude toward AI (RQ4).

METHODS

Data Collection

This research utilized data from the 2023 Digital Divide Survey (DDS), which was sponsored by the Ministry of Science and ICT and conducted by the National Information Society Agency (NIA) in South Korea. The DDS is a nationwide study of the Korean population aged 7 and older, which has been conducted every year since 2002 to investigate the advances made in policies aimed at mitigating the digital divide through time-series analysis. In this study, the total sample collected through a multi-stage stratified sampling method in 16 metropolitan areas in South Korea (n = 15,000) consisted of 7,000 participants for general consumers and 8,000 participants belonging to various categories, including low-income individuals (n = 2,200), people with disabilities (n = 2,200), farmers (n =2,200), North Korean defectors (n = 700), and marriage immigrants (n = 700). In this research, we mainly focused on the low-income individuals in South Korea. Specifically, low-income individuals are recipients supported from the National Basic Livelihood Security System in South Korea, who are aged 7 to 74 years. Of a total sample of 2,200 respondents, this research chose the low-income respondents who were aware of generative AI tools such as ChatGPT, Google Gemini, and so on. Hence, the final sample size was 770. Overall, 59.9% of respondents had prior experience using various AI-based services (e.g., generative AI tools, healthcare, banking, smart home, transportation, education, etc.), while 33.6% of respondents had prior usage experience with generative AI tools.

Specifically, the total sample (n = 770) was composed of 372 women (48.3%) and 398 men (51.7%). The age profile (M = 37.54, SD = 17.77) was as follows: youngest age groups of less than 20 years = 29.0%; 20 to 29 years = 14.2%; 30 to 39 years = 9.7%; 40 to 49 years = 15.8%; 50 to 59 years = 18.2%; 60 to 69 years = 10.9%; and 70 to 79 years = 2.2%. Majority of the respondents had high school education only (50.6%) or less (33.2%), and 16.2% with a college/university degree or postgraduate degree. Regarding the monthly household income, 19.7% reported income of less than $1,000; 46.1% fell within an income range of $1,000 to $1,990; 31.0% were in the $2,000 to $2,990 range; 2.7% were in the $3,000 to $3,990 range; 0.1% were in the $4,000 to $4,990 range; 0.1% were in the $5,000 to $5,990 range; and 0.1% were in the $6,000 to $6,990 range.

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Measures

This research includes items relevant to respondents' prior AI experience, perceptions of and general attitude toward AI, and attitude toward generative AI tools (see **Table 1**). The items measuring variables were obtained from previous related studies. Specifically, the respondents' prior AI experience is measured and dummy coded (0 = No, 1 = Yes). Regarding the respondents' perceived usefulness of AI [33], general attitude toward AI [33], and cognitive attitude toward generative AI tools [34], all the variables are assessed with a 4-point Likert scale (1: strongly disagree, 4: strongly agree). Among these variables, the respondents' cognitive attitude toward generative AI tools was measured using a single item. In previous research, for doubly concrete constructs (e.g., attitude, purchase intention)—that is, they have a simple, clear object and a single and single-meaning attribute (e.g., liking), single-item measures demonstrated predictive validity equal to that of multiple-item measures, even though the overwhelming practice in academic research is to measure them with multiple items [35-37]. Moreover, researchers may decide to opt for single-item measures in light of their manifold practical advantages [38, 39].

Apart from study variables, respondents' demographics (i.e., gender, age, education level, and monthly household income) and their prior experience in using generative AI tools can also affect their attitude toward generative AI tools. Research suggests that there are gender differences in how personality relates to technology use and its service [40]; and that younger people tend to show more positive new technology acceptance than older people [41]. It has also been suggested that prior experience makes a significant impact on how one develops his/her attitudes toward a new technology [24]. Thus, we have controlled the effects of the respondents' usage experience and demographic variables. Prior experience in using generative AI tools is measured and dummy coded (0 = No, 1 = Yes). Regarding demographic variables, gender is dummy coded (0 = male, 1 = female); age is assigned 1 for "less than 20", "20-29" is assigned 2, "30-39" is assigned 3, "40-49" is assigned 4, "50-59" is assigned 5, "60-69" is assigned 6, and "above 70" is assigned 7; education level is measured using four categories: (1) less than middle school, (2) middle school, (3) high school, and (4) college/university or postgraduate; for monthly household income, 11 categories are provided: (1) less than $1,000 and (11) $10,000 or more.

Data Analysis

Normal distribution of data was tested with the confirmation of skewness and kurtosis (see **Table 2**). Since all the data were collected through a single method, i.e., survey, from the same respondents at one point in time, the potential for common method biases thus needed to be addressed. This research employed procedural and statistical techniques to address the issue. Before the survey, respondents were fully given freedom of choice and freedom of expression assuring that the responses will be kept highly confidential. They were also reassured that there were no right or wrong answers and were explicitly asked to answer questions honestly. Statistically, in the Harman's single factor test [42], all the items used for this study were entered into a principal component analysis (PCA) with unrotated factor solution to identify if a single factor emerges or one general factor accounts for more than 50% of the covariation. The results under the condition of extracting one factor showed that the factor loadings explained only 41.643% of the variance and not the majority. This indicated that common method biases were not a likely contaminant of the results.

Next, to execute the exploratory factor analysis (EFA), this research conducted principal axis factoring (PAF) analysis with direct oblique (oblimin) rotation (Delta = 0) on all items to estimate empirically the number of factors extracted. For the items, the Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO) measure was .765, indicating that the sample was adequate for EFA. The Bartlett's test for sphericity was significant (1185.308, p = .000), indicating that EFA was appropriate. Based on the results, two factors were labelled as perceived usefulness of AI (4 items) and general attitude toward AI (2 items). Based on the results of EFA, reliability (internal consistency) was assessed through Cronbach's alpha (α), McDonald's omega (ω), and Pearson's correlation coefficient (r). Factor loadings for all the items and the results of reliability analyses are shown in **Table 1**. In summary, the results of EFA and reliability analyses correspond to a theoretical definition of the items of each variable under investigation. Descriptive statistics and correlations between the variables are shown in **Table 2**. Pearson's correlation coefficients as well as biserial

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correlation coefficients were calculated to examine the bivariate correlations of prior AI experience, perceived usefulness of AI, general attitude toward AI, and attitude toward generative AI tools.

Table 1. Measurement Scales, Factor Loadings, and Reliability for Variables

Variable /Items	Measurement Scales	Factor Loading
Perceived Usefulness of AI (Cronbach's α = .821; McDonald's ω = .823)		
Item1	AI will make our life convenient.	.574
Item2	AI will create more economic opportunities such as cost savings and new income.	.460
Item3	AI will allow us to receive better information services.	.643
Item4	AI will provide us with better information.	.661
General Attitude toward AI (r = .745; Cronbach's α = .851)		
Item1	AI will have a positive impact on humans and society.	-.771
Item2	Changes brought about by AI will have a positive effect on me.	-.874
Attitude toward Generative AI Tools		
Item1	Generative AI tools are beneficial to my life.	

Table 2. Descriptive Statistics and Correlations among the Variables

	1	2	3	4
1. Prior AI Experience	-			
2. Perceived Usefulness of AI	.241[b]	-		
3. General Attitude toward AI	.139[b]	.481[a]	-	
4. Attitude toward Generative AI Tools	.145[b]	.256[a]	.208[a]	-
Mean	-	3.20	3.10	2.94
S.D.	-	0.43	0.43	0.80
Skewness	-	-0.318	0.155	-0.709
Kurtosis	-	0.488	2.052	0.409

Note: a = Pearson's correlation coefficients; b = biserial correlation coefficients; $p < .001$ for all correlations.

RESULTS

As stated, a hierarchical multiple regression analysis was performed to answer the RQ1. First, the respondents' demographic variables and prior usage experience with generative AI tools were entered as the first block (Step 1). Then, prior AI experience was entered as the second block (Step 2). For the third step (Step 3), the two potential mediating variables (i.e., perceived usefulness of AI, general attitude toward AI) were included. All Variance Inflation Factors (VIFs) are lower than 2, suggesting that multicollinearity should not be a problem. Regarding the RQ1, the results from the hierarchical regression analysis are summarized in **Table 3**. In Step 1, the control variables (i.e., demographic variables and prior usage experience with generative AI tools) explain 11.0% of variance ($F(5, 764) = 18.907$, $p = .000$, $R^2 = .110$). Specifically, age and prior usage experience with generative AI tools are significant predictors of attitude toward generative AI tools. In Step 2 ($\triangle F(1, 763) = 0.278$, $p = .598$, $\triangle R^2 = .000$), the effect of prior AI experience is not statistically significant ($p > .10$). The full regression model in Step 3 ($\triangle F(2, 761) = 13.062$, $p = .000$, $\triangle R^2 = .030$) shows that the perceive usefulness of AI ($\beta = 0.130$, $p = .001$) and general attitude toward AI ($\beta = 0.085$, $p = .027$) are positively associated with the attitude toward generative AI tools. In sum, the perceived usefulness of AI as well as the general attitude toward AI is positively associated with the attitude toward generative AI tools.

Table 3. Results of Hierarchical Regression Analysis (n = 770)

Independent Variables	Dependent Variable: Attitude toward Generative AI Tools					
	Step 1		Step 2		Step 3	
	B	β	B	β	B	β
Gender (female)	0.047	0.030	0.047	0.030	0.047	0.030
Age	-0.066***	-0.155***	-0.065***	-0.153***	-0.043**	-0.102**
Education	-0.002	-0.002	-0.003	-0.003	-0.022	-0.023
Monthly Household Income	-0.028	-0.028	-0.030	-0.031	-0.022	-0.023
Prior Usage Experience with Generative AI Tools	0.460***	0.274***	0.447***	0.266***	0.394***	0.234***
Prior AI Experience			0.032	0.020	-0.005	-0.003
Perceived Usefulness of AI					0.241***	0.130***
General Attitude toward AI					0.158*	0.085*
R^2	.110		.110		.140	
$\triangle R^2$	.110		.000		.030	
$\triangle F$	18.907***		0.278		13.062***	

Note: B = unstandardized coefficients; β = standardized coefficients; **p* < .05, ***p* < .01, ****p* < .001.

In particular, as noted in the RQ4, this research examines whether the relationship between prior AI experience and attitude toward generative AI tools is mediated by the perceived usefulness of AI and general attitude toward AI. Thus, as presented in **Figure 1**, serial mediation yields a "three-path mediation model" [43]. Our remaining research questions (RQs 2-4) were examined with a bootstrapping of 5,000 times and a 95% confidence interval, by utilizing the PROCESS macro (Model 6) developed by Hayes [43]. First, we tested the total effect of prior AI experience on attitude toward generative AI tools (c), controlling for the effects of demographic variables and prior usage experience of generative AI tools. The results show a nonsignificant relationship (b = 0.032, SE = 0.061, *p* = .598, 95% CI = [-0.088, 0.153]). Regarding the RQ2, the test revealed that prior AI experience predicted the perceived usefulness of AI (b = 0.118, SE = 0.033, *p* = .000, 95% CI = [0.054, 0.182]) and that the perceived usefulness predicted the attitude toward generative AI tools (b = 0.241, SE = 0.075, *p* = .001, 95% CI = [0.094, 0.387]). Thus, the mediation test results in a statistically significant indirect effect; that is, the indirect effect for the prior AI experience → perceived usefulness of AI → attitude toward generative AI tools pathway was positive and significant (b = 0.028, SE = 0.012, 95% CI = [0.008, 0.055]).

Regarding the RQ3, the test revealed that the effect of prior AI experience on the general attitude toward AI was not significant (b = 0.003, SE = 0.031, *p* = .919, 95% CI = [-0.057, 0.064]), while the general attitude toward AI predicted the attitude toward generative AI tools (b = 0.158, SE = 0.072, *p* = .027, 95% CI = [0.018, 0.299]). Thus, the mediation test results in a statistically nonsignificant indirect effect; that is, the indirect effect for the prior AI experience → general attitude toward AI → attitude toward generative AI tools pathway was not significant (b = 0.001, SE = 0.006, 95% CI = [-0.011, 0.013]).

Regarding the RQ4, the direct effect of the perceived usefulness of AI on general attitude toward AI was found to be significantly positive (b = 0.443, SE = 0.034, *p* = .000, 95% CI = [0.376, 0.510]); more importantly, the indirect effect for the prior AI experience → perceived usefulness of AI → general attitude toward AI → attitude toward generative AI tools pathway was positive and significant (b = 0.008, SE = 0.005, 95% CI = [0.001, 0.019]), which indicates that the prior AI experience sequentially increases the perceived usefulness of AI, general attitude toward AI, and attitude toward generative AI tools. The mediation test results are summarized in **Table 4**.

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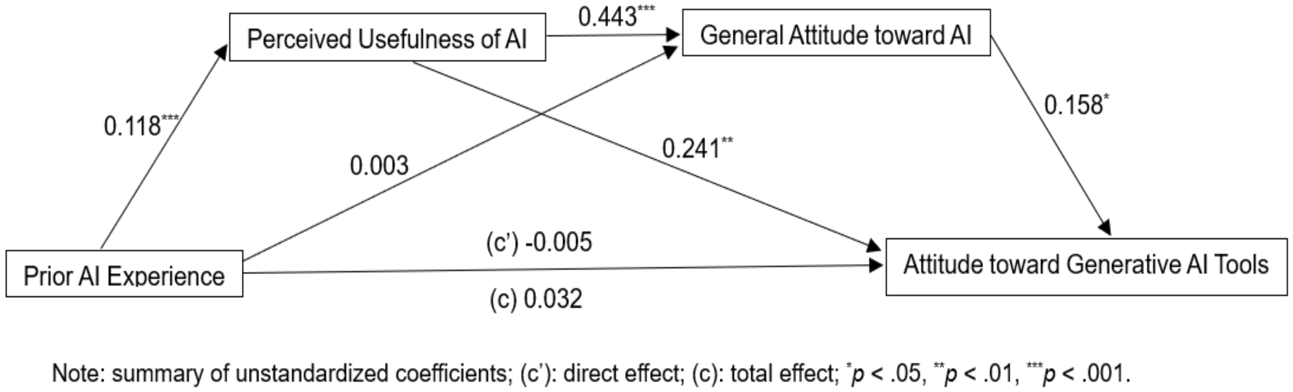

Figure 1. Three-Path Mediation Model

Table 4. Sequential Mediation Results (n = 770)

Independent Variables	Perceived Usefulness of AI B	Perceived Usefulness of AI β	General Attitude toward AI B	General Attitude toward AI β	Attitude toward Generative AI Tools B	Attitude toward Generative AI Tools β
Gender (female)	0.015 (0.029)	0.017	-0.030 (0.027)	-0.036	0.047 (0.054)	0.030
Age	-0.059*** (0.008)	-0.256***	-0.023** (0.008)	-0.099**	-0.043** (0.016)	-0.102**
Education	0.054** (0.019)	0.101**	0.015 (0.018)	0.029	-0.023 (0.035)	-0.023
Monthly Household Income	-0.014 (0.019)	-0.026	-0.022 (0.018)	-0.042	-0.022 (0.035)	-0.023
Prior Usage Experience with Generative AI Tools	0.150*** (0.033)	0.166***	0.041 (0.032)	0.045	0.394*** (0.063)	0.235***
Prior AI Experience	0.118*** (0.033)	0.274***	0.003 (0.031)	0.007	-0.005 (0.061)	-0.006
Perceived Usefulness of AI	-	-	0.443*** (0.034)	0.444***	0.241** (0.075)	0.130**
General Attitude toward AI	-	-	-	-	0.158* (0.072)	0.085*
R^2	.149		.244		.140	
F	22.289***		35.095***		15.480***	
df	6, 763		7, 762		8, 761	

Note: B = unstandardized coefficients; β = standardized coefficients; The numbers in parentheses are standard errors; $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

DISCUSSION

In this research, with the huge popularity of generative AI tools such as ChatGPT, Google Gemini, and so on, we explore the individual factors impacting the low-income Koreans' attitudes toward generative AI tools. Specifically, we first examine whether low-income Korean individuals' prior AI experience, perceived usefulness of AI, and general attitude toward AI influence their attitudes toward generative AI tools, controlling for the effects of demographic variables and prior usage experience with generative AI tools (RQ1). Second, we examine whether the prior AI experience affects the attitude toward generative AI tools via the perceived usefulness of AI (RQ2). Third, we examine whether the prior AI experience influences the attitude toward generative AI tools via the general attitude toward AI (RQ3). Fourth, we examine whether the relationship between prior AI experience and attitude toward generative AI tools is serially mediated by the perceived usefulness of AI and general attitude toward AI (RQ4).

To answer the RQ1, a hierarchical multiple regression analysis was first performed using the low-income Koreans who were aware of the generative AI tools. The results indicate that both the perceived usefulness of AI and general attitude toward AI are positively associated with the attitude toward generative AI tools. Second, regarding the RQ2, we analyzed the mediating role of the perceived usefulness of AI between the prior AI experience and the attitude toward generative AI tools. The results reveal that the prior AI experience affects the attitude toward generative AI tools via the perceived usefulness of AI. Third, regarding the RQ3, we analyzed the role of general attitude toward AI as a mediator between the prior AI experience and the attitude toward generative AI tools. The results reveal that the indirect effect of prior AI experience on the attitude toward generative AI tools, via the general attitude toward AI, is not statistically significant. Fourth, we used the serial mediation approach to address the RQ4. The results indicate that the relationship between the prior AI experience and the attitude toward generative AI tools is serially mediated by the perceived usefulness of AI and general attitude toward AI.

Given that low-income countries face multiple challenges in harnessing its benefits, exacerbating existing global disparities in technology adoption [10], the findings contribute to a comprehensive understanding of the factors influencing the low-income individuals' attitudes toward the generative AI tools. In addition, our findings not only supplement prior studies but also provide a theoretical basis for systematic research on individuals' prior experience, perceptions, and attitudes toward AI impacting their attitudes toward generative AI tools. Moreover, from the managerial perspective, the research findings are expected to be of key essence to practitioners and policymakers from various fields, providing invaluable insight into enhancing the low-income individuals' attitudes toward the generative AI tools. Specifically, it is necessary to increase low-income individuals' familiarity or usage experience with AI and widely inform low-income individuals about the usefulness of AI through capitalizing online resources or policy-driven investments (e.g., online education platforms, training programs, tech communities, etc.), which will in turn make them find generative AI tools beneficial to their daily lives for a variety of tasks. It is also important to encourage them to have favorable attitudes toward AI and increase their satisfaction with AI by utilizing the potential of generative AI-driven marketing.

Although this research has some important implications for academic researchers and practitioners, it is not without limitations. We present possible research directions for future studies. First, it would be good for future research to examine if the findings are applicable to other groups of people (e.g., general consumers, people with disabilities, etc.). Second, this study solely focused on the low-income Korean respondents who were aware of generative AI tools, which limits generalization of the results. Although the use of a random and representative sample of low-income Koreans significantly improves the external validity of results, they are only generalizable within Korea. As such, replication of this work in various countries is recommended to generalize the findings. Third, future research could examine other potential factors impacting the attitude toward generative AI tools. Fourth, future research could consider other various dependent variables (e.g., affective attitude, behavioral intention, etc.), which will provide more insights into the generative AI tools.

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