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The Effects of Digital Self-Efficacy, Perceived Benefits of AI and Social Capital on Attitude toward Generative AI Tools: A Moderated Mediation Model

Moon-Yong Kim[1]
[1]*Professor, College of Business, Hankuk University of Foreign Studies, Seoul, South Korea*
moonyong@hufs.ac.kr

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ABSTRACT

With the huge popularity of generative Artificial Intelligence (AI) tools utilized to search for information (e.g., ChatGPT, Google Gemini, etc.), they have recently increased the power of consumer marketing and the effectiveness of customer service. The present research aims to explore the factors influencing the individuals' attitudes toward the generative AI tools. Specifically, we first examine whether individuals' digital self-efficacy and perceived benefits of AI affect their attitudes toward the generative AI tools. Second, we examine whether the digital self-efficacy influences the attitude toward the generative AI tools via the perceived benefits of AI. Third, we examine whether the mediation effect of the perceived benefits of AI on the relationship between the digital self-efficacy and attitude toward the generative AI tools is moderated by two types of social capital—bonding social capital and bridging social capital, respectively. To answer the research questions, we conducted some statistical analyses (i.e., hierarchical multiple regression analysis, mediation analysis, and moderated mediation analysis) using the Koreans who were aware of the generative AI tools (N = 3,564). The results indicate that (1) the digital self-efficacy as well as the perceived benefits of AI are positively associated with the attitude toward the generative AI tools; (2) the digital self-efficacy impacts the attitude toward the generative AI tools via the perceived benefits of AI; and (3) the indirect effect of the digital self-efficacy on the attitude toward the generative AI tools, via the perceived benefits of AI, is weaker at a high (vs. low) level of social capital. The findings provide important implications to enhance the individuals' attitudes toward the generative AI tools.

Keywords: Generative AI, Digital Self-Efficacy, Perceived Benefits, Social Capital, 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 consumers think, behave and live in this post-pandemic era. 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 example, 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]. In particular, when it comes to searching for information, such AI-powered chatbots as ChatGPT and Google Gemini apply generative AI techniques to provide algorithm-generated conversational responses to question prompts [4]. That is, generative AI tools such as ChatGPT and Google Gemini provide immediate answers and responses to almost every question users ask for, like Google and Yahoo search engines. ChatGPT developed by OpenAI is a large

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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 are utilized in various fields such as education, information retrieval, business, and e-commerce, offering useful services [5].

In this research, focusing on the generative AI tools utilized to search for information (e.g., ChatGPT, Google Gemini, etc.), we explore the potential factors affecting the individuals' attitudes toward the generative AI tools. Specifically, we first examine whether individuals' digital self-efficacy and perceived benefits of AI influence their attitudes toward the generative AI tools. Second, we examine whether the digital self-efficacy affects the attitude toward the generative AI tools via the perceived benefits of AI. Third, we examine whether the mediation effect of the perceived benefits of AI on the association between the digital self-efficacy and attitude toward the generative AI tools is moderated by two types of social capital—bonding social capital and bridging social capita, respectively.

LITERATURE REVIEW AND RESEARCH QUESTION

Digital self-efficacy is defined as a judgment of one's capability to use a digital device [6]. It is concerned with one's judgment of what one can do with those abilities [7]. Many researchers have studied it as a psychological factor affecting individuals' decisions to accept and use new technology [6, 8]. For instance, individuals with higher levels of self-efficacy have a more positive perspective on information and communication technology (ICT) and are more likely to use and continue to use digital devices.

Perceived benefits of products/services refer to the extent to which consumers perceive the products/services as being capable of facilitating judgment or purchase decisions [9]. 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 [10]. Users are more likely to accept and adopt new technology if they perceive it as beneficial in achieving their goals or tasks [11]. If individuals perceive AI as beneficial, they are more likely to be motivated to use it [12]. In the technology acceptance model (TAM), perceived usefulness is a crucial factor influencing an individual's attitude and intention toward technology usage [13]. The model suggests that individuals are more inclined to adopt and utilize technology if they believe it aids in accomplishing their goals and tasks [14].

It has recently been suggested in the consumer research literature that consumer attitudes are inherently bidimensional because consumer purchase goods and services and perform consumption behaviors for two basic reasons: instrumental/utilitarian vs. affective/hedonic reasons [15]. In a similar vein, the distinction between instrumental/cognitive versus experiential/affective components of attitudes is long established [16]. The cognitive component of attitude (or cognitive attitude) is considered to be the evaluation implied by cognition about an attitude object [17], while the affective component of attitude (or affective attitude) is considered to be the evaluation implied by feelings (or emotions) about an attitude object [18]. 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 [19, 20]. Hence, if individuals perceive AI to be beneficial, they are likely to have a positive attitude toward AI-based products or services, which increases their intention to use them [21].

Social capital is generally defined as the positive effect of the interaction among participants on a social network [22, 23]. Based on the social ties, social capital was initially separated into two dimensions: bonding social capital and bridging social capital [24]. These two types of social capital can be differentiated by two aspects: tie strength and type of resources provided. Bonding social capital comes from strong social ties, whereas bridging social capital is embedded in weak social ties. More specifically, bonding social capital refers to resources from strong ties, including family members and close friends, which are characterized by higher levels of trust and intimacy. They are well-defined groups with small-scale interactions. Thus, people are likely to get greater emotional support and spontaneous help from bonding capital. Bridging social capital refers to resources from weak ties that connect different clusters within a network, such as acquaintances with little intimacy and closeness. As weak ties work as a bridge that connects relationships in different clusters and creates a pathway to close structural holes between two originally unconnected groups, they are able to provide access to novel information and allow for mobility and the diffusion of heterogeneous information [25]. Previous research has shown that structural social capital in the form of contacts with others (i.e., bonding social capital, bridging social capital) was negatively associated with AI

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perception [26]. That is, since bonding social capital as well as bridging social capital means daily social contacts with neighbors and with friends and acquaintances in a neighborhood, it may represent homophily or networks among people. Thus, those with close contacts with others may have difficulties in adopting new "relationship" with AI.

Drawing on the prior findings, therefore, we first examine whether individuals' digital self-efficacy and perceived benefits of AI influence their attitudes toward the generative AI tools, controlling for the effects of demographic variables and prior usage experience with generative AI tools (RQ1). Second, we examine whether the digital self-efficacy affects the attitude toward the generative AI tools via the perceived benefits of AI (RQ2). Third, we examine whether the mediation effect of the perceived benefits of AI on the association between the digital self-efficacy and attitude toward the generative AI tools is moderated by two types of social capital—bonding social capital (RQ3) and bridging social capital (RQ4), respectively; that is, we examine whether the mediation effect of the perceived benefits of AI on the association between the digital self-efficacy and attitude toward the generative AI tools is weaker at a high (vs. low) level of social capital.

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 digital information gap of vulnerable groups. The data (N = 7,000) are collected through a multi-stage stratified sampling method for general consumers in 16 metropolitan areas in South Korea. This research chose the respondents who were aware of generative AI tools such as ChatGPT and Google Gemini. That is, among the total sample of 7,000 respondents, 50.9% reported awareness of generative AI tools such as ChatGPT and Google Gemini. Hence, the final sample size was 3,564. Overall, 43.0% of respondents had prior usage experience with generative AI tools, while 70.9% of respondents had prior experience using a variety of AI-based services including generative AI tools, healthcare, banking, smart home, education, transportation, and so on.

Specifically, the total sample (N = 3,564) was composed of 1,613 women (45.3%) and 1,951 men (54.7%). The age profile (M = 38.31, SD = 15.614) was as follows: youngest age groups of less than 20 years = 15.1%; 20 to 29 years = 19.9%; 30 to 39 years = 19.8%; 40 to 49 years = 19.6%; 50 to 59 years = 15.5%; 60 to 69 years = 7.7%; 70 to 79 years = 2.2%; and 80 years and older = 0.3%. Majority of the respondents had a college/university degree or postgraduate degree (50.8%) or high school education only (35.8%), and 13.4% with less than high school graduation. Regarding the monthly household income, 1.6% of the respondents reported income of less than $1,000; 3.1% fell within an income range of $1,000 to $1,990; 9.1% were in the $2,000 to $2,990 range; 17.0% were in the $3,000 to $3,990 range; 19.6% were in the $4,000 to $4,990 range; 21.6% were in the $5,000 to $5,990 range; 14.2% were in the $6,000 to $6,990 range; 6.7% were in the $7,000 to $7,990 range; 4.6% were in the $8,000 to $8,990 range; and only 2.4% reported income exceeding $9,000.

Measures

This research includes items relevant to respondents' digital self-efficacy, perceptions of AI, social capital (bonding social capital, bridging social capital), and attitude toward generative AI tools (see Table 1). The items measuring variables were obtained from previous related studies. Specifically, regarding the respondents' digital self-efficacy [27], perceived benefits of AI [28], social capital [22, 24], and cognitive attitude toward generative AI tools [29], 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 [30-32]. Moreover, researchers may decide to opt for single-item measures in light of their manifold practical advantages [33, 34].

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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. 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, "70-79" is assigned 7, and "above 80" is assigned 8; 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 [35], 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 50% of the covariation. The results under the condition of extracting one factor showed that the factor loadings explained only 27.973% of the variance, which is lower than the threshold of 50%. 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 the 20 items relevant to the four variables (i.e., digital self-efficacy, perceived benefits of AI, bonding social capital, bridging social capital) to estimate empirically the number of factors extracted. For the items, the Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO) measure was .886, indicating that the sample was adequate for EFA. The Bartlett's test for sphericity was significant (20239.612, p = .000), indicating that EFA was appropriate. Based on the results, we confirmed that the three factors were labelled as digital self-efficacy (4 items), perceived benefits of AI (6 items), bonding social capital (5 items), and bridging social capital (5 items). Based on the results of EFA, reliability (internal consistency) was assessed through Cronbach's alpha (α) and McDonald's omega (ω). Factor loadings for all the items and the results of reliability analyses are shown in Table 1. In sum, 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 were calculated to examine the bivariate correlations of digital self-efficacy, perceived benefits of AI, bonding social capital, bridging social capital, and attitude toward generative AI tools.

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

Variable /items	Measurement scales	Factor loading
Digital Self-Efficacy (Cronbach's α = .818; McDonald's ω = .824)		
Item1	I am confident in learning digital devices.	.834
Item2	I am confident in using digital devices.	.758
Item3	I can quickly figure out how to use new digital devices.	.747
Item4	If a problem occurs while using a digital device, I solve the problem on my own without the help of others.	.535
Perceived Benefits of AI (Cronbach's α = .746; McDonald's ω = .727)		
Item1	AI will make our life convenient.	.468

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Item2	AI will create more economic opportunities such as cost savings and new income.	.362
Item3	AI will allow us to receive better information services.	.375
Item4	AI will provide us with better information.	.376
Item5	AI will have a positive effect on humans and society.	.771
Item6	Changes brought about by AI will have a positive impact on me.	.785
Bonding Social Capital (Cronbach's α = .701; McDonald's ω = .704)		
Item1	I have someone who can help me solve my problem.	.551
Item2	I have someone I can turn to for advice when making very important decisions.	.500
Item3	I have someone I can comfortably talk to about intimate personal matters.	.477
Item4	I have someone I can trust with my important work.	.504
Item5	People will help me fight against injustice.	.415
Bridging Social Capital (Cronbach's α = .746; McDonald's ω = .745)		
Item1	Interacting with people makes me feel connected to the larger world.	.494
Item2	When I interact with people, I feel like everyone in the world is connected.	.500
Item3	I am willing to spend time involved in community activities.	.429
Item4	Interacting with people allows me to talk to new people.	.627
Item5	Interacting with people always allows me to meet new people.	.633
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	5
1. Digital Self-Efficacy	-				
2. Perceived Benefits of AI	.455	-			
3. Bonding Social Capital	.364	.348	-		
4. Bridging Social Capital	.387	.351	.529	-	
5. Attitude toward Generative AI Tools	.251	.304	.112	.165	-
Mean	3.09	3.21	3.08	2.97	3.08
S.D.	0.58	0.39	0.43	0.46	0.70
Skewness	-0.694	-0.361	-0.445	-0.462	-0.585
Kurtosis	0.564	0.833	1.023	0.838	0.636

Note: $p < .001$ for all correlations.

RESULTS

As stated, a hierarchical multiple regression analysis was performed to answer the RQ1. First, the demographic variables were entered as the first block (Step 1). Then respondents' prior usage experience with generative AI tools was entered as the second block (Step 2). For the third step (Step 3), the two independent variables (i.e., digital self-efficacy, perceived benefits of AI) were included. All Variance Inflation Factors (VIFs) are lower than 2, suggesting that multicollinearity should not be a problem for this study.

Results from the hierarchical regression analysis are summarized in Table 3. In Step 1, demographic variables alone explain 3.0% of variance ($F(4, 3559) = 27.544$, $p = .000$, $R^2 = .030$). Specifically, gender, age, education, and monthly household income are all significant predictors of attitude toward generative AI tools. In Step 2 ($\triangle F(1, 3558) = 78.313$, $p = .000$, $\triangle R^2 = .021$), prior usage experience with generative AI tools ($\beta = 0.149$, $p = .000$) is positively associated with the attitude toward generative AI tools. The full regression model in Step 3 ($\triangle F(2, 3556) = 157.294$, $p = .000$, $\triangle R^2 = .077$) shows that both digital self-efficacy ($\beta = 0.114$, $p = .000$) and the perceive benefits of AI ($\beta = 0.232$, $p = .000$) are positively associated with the attitude toward generative AI tools. In addition, regarding the effects of

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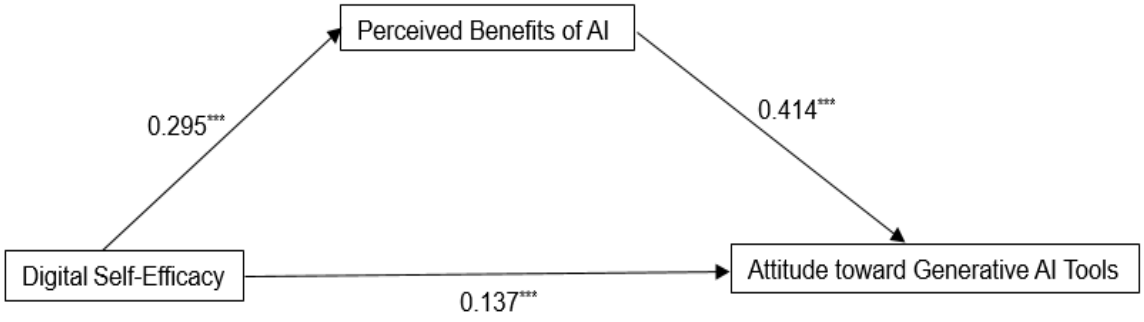
demographic variables, the results pertaining to the effects of age, gender, and monthly household income in Step 2 may be spurious, given that the effects are lessened to non-significant ($p > .05$). In summary, regarding the RQ1, the perceived benefits of AI as well as the digital self-efficacy is positively associated with the attitude toward the generative AI tools.

Table 3. Results of Hierarchical Regression Analysis (n = 3,564)

	Dependent Variable: Attitude toward Generative AI Tools					
Independent Variables	Step 1		Step 2		Step 3	
	B	β	B	β	B	β
Gender (Female)	-0.059*	-0.042*	-0.055*	-0.039*	-0.033	-0.023
Age	-0.066***	-0.153***	-0.052***	-0.121***	-0.008	-0.018
Education	0.040**	0.046**	0.028	0.032	-0.014	-0.017
Monthly Household Income	0.020**	0.056**	0.017**	0.048**	0.011	0.029
Prior Usage Experience with Generative AI Tools			0.209***	0.149***	0.185***	0.131***
Digital Self-Efficacy					0.137***	0.114***
Perceived Benefits of AI					0.414***	0.232***
R^2	.030		.051		.128	
$\triangle R^2$	.030		.021		.077	
$\triangle F$	27.544***		78.313***		157.294***	

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

Second, regarding the RQ2, we analyzed the role of perceived benefits of AI as a mediator between the digital self-efficacy and the attitude toward generative AI tools. Using the PROCESS macro (Model 4, 5,000 bootstrapped samples) [36], we conducted a mediation analysis including all our control variables (i.e., demographic variables, prior usage experience with generative AI tools) as covariates to test whether the digital self-efficacy influences the attitude toward generative AI tools via the perceived benefits of AI. Results showed that the digital self-efficacy had a positive and significant effect on the perceived benefits of AI (b = 0.295, SE = 0.012, t = 25.541, $p = .000$, 95% CI = [0.272, 0.317]); in turn, the digital self-efficacy (b = 0.137, SE = 0.024, t = 5.792, $p = .000$, 95% CI = [0.090, 0.183]) as well as the perceived benefits of AI (b = 0.414, SE = 0.032, t = 13.131, $p = .000$, 95% CI = [0.352, 0.475]) had a positive and significant impact on the attitude toward generative AI tools. Crucially, bootstrapping analysis with 5000 resamples excluded zero for the proposed indirect mediation path (Mediation Index = 0.122, Boot SE = 0.012, 95% CI = [0.099, 0.146]; see Figure 1). In sum, concerning the RQ2, the perceived benefits of AI mediate the association between the digital self-efficacy and the attitude toward generative AI tools.



Note: indirect effect of X on Y via the mediator: b = 0.122, 95% CI = 0.099, 0.146; *$p < .05$, **$p < .01$, ***$p < .001$.

Figure 1. Results of Mediation Analysis

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Third, regarding the RQ3, we investigate whether bonding social capital moderates the relationship between digital self-efficacy and attitude toward generative AI tools via the perceived benefits of AI. Hayes' PROCESS macro Model 14 (i.e., the moderated mediation test introduced by Hayes; 5,000 bootstrapped samples) was performed to address the research question. Moderated mediation is assumed when the indirect effect of digital self-efficacy on the attitude toward generative AI tools via the perceived benefits of AI differ significantly between one standard deviation score below (-1SD) and above (+1SD) the mean value of bonding social capital. In this analysis, digital self-efficacy (independent variable), perceived benefits of AI (mediator), and bonding social capital (moderator) were mean-centered, with low and high levels of bonding social capital operationalized as one SD below (Mean-1SD) and above the mean (Mean+1SD), respectively. Prior to showing the moderated mediation effect, PROCESS macro Model 14 initially demonstrated a significant two-way interaction effect between the perceived benefits of AI and bonding social capital on the attitude toward generative AI tools after controlling for potential covariates (b = -0.191, SE = 0.058, t = -3.291, p = .001, 95% CI = [-0.305, -0.077]). As presented in Figure 2, the simple slope tests demonstrated that among respondents with lower (Mean-1SD = 2.66) levels of bonding social capital, the positive association between the perceived benefits of AI and the attitude toward generative AI tools became stronger (b = 0.499, SE = 0.039, t = 12.819, p = .000, 95% CI = [0.422, 0.575]), compared with those with moderate (Mean = 3.08) levels of bonding social capital (b = 0.417, SE = 0.032, t = 12.903, p = .000, 95% CI = [0.354, 0.481]) and higher (Mean+1SD = 3.51) bonding social capital (b = 0.336, SE = 0.042, t = 7.920, p = .000, 95% CI = [0.253, 0.419]). The results of the Johnson-Neyman method demonstrated that there were no statistical significance transition points within the observed range of the moderator. In sum, this implies that those with higher bonding social capital may have relatively lower attitude toward generative AI tools even with same extent of the perceived benefits of AI as others.

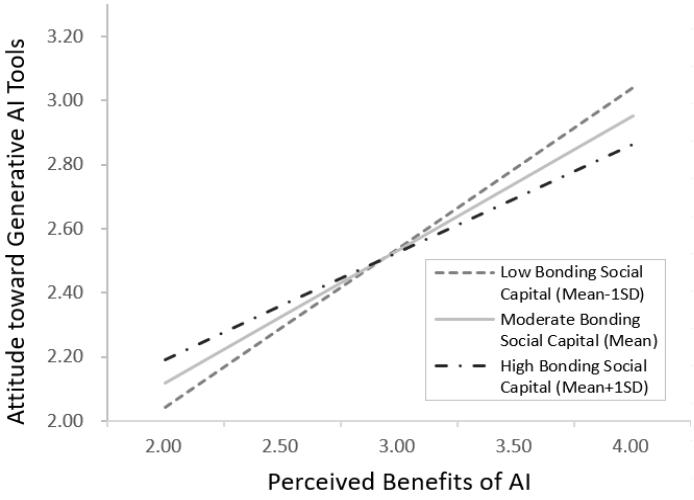

Figure 2. Results of Moderation Analysis

In addition to the two-way interaction, results further demonstrated a significant moderated mediation model, in which the association between digital self-efficacy and the attitude toward generative AI tools mediated through the perceived benefits of AI was further moderated by bonding social capital (Moderated Mediation Index = -0.056, Boot SE = 0.021, 95% CI = [-0.099, -0.017]). That is, the perceived benefits of AI mediate the effect of digital self-efficacy on the attitude toward generative AI tools, and this indirect effect is moderated by bonding social capital. Specifically, as shown in Figure 3, among respondents with lower (Mean-1SD) levels of bonding social capital, the indirect effect of digital self-efficacy on the attitude toward generative AI tools was significant and stronger (b = 0.147, Boot SE = 0.016, 95% CI = [0.118, 0.178]), compared with those with moderate (Mean) levels of bonding social capital (b = 0.123, Boot SE = 0.013, 95% CI = [0.099, 0.148]) and higher (Mean+1SD) levels of bonding social capital (b = 0.099, Boot SE = 0.015, 95% CI = [0.070, 0.128]). In sum, the moderated mediation effect was present both in the high and low levels of bonding social capital. In general, the finding implies that the indirect effect of digital self-efficacy on attitude toward generative AI tools, via the perceived benefits of AI, significantly decreases as bonding social capital increases from low level to high level.

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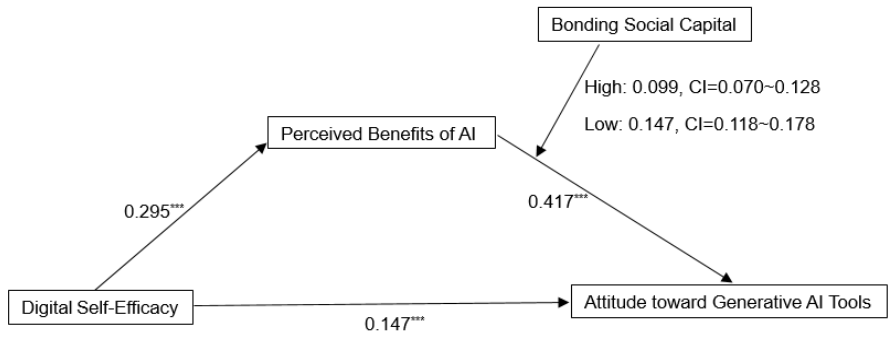
Fourth, regarding the RQ4, we investigate whether bridging social capital moderates the relationship between digital self-efficacy and attitude toward generative AI tools via the perceived benefits of AI. As in the analysis to answer the RQ3, Hayes' PROCESS macro Model 14 was also performed to address the RQ4. In this analysis, digital self-efficacy (independent variable), perceived benefits of AI (mediator), and bridging social capital (moderator) were mean-centered, with low and high levels of bridging social capital operationalized as one SD below (Mean-1SD) and above the mean (Mean+1SD), respectively. Prior to showing the moderated mediation effect, PROCESS macro Model 14 initially demonstrated a significant two-way interaction effect between the perceived benefits of AI and bridging social capital on the attitude toward generative AI tools after controlling for potential covariates (b = -0.316, SE = 0.050, t = -6.303, p = .000, 95% CI = [-0.414, -0.218]). As shown in Figure 4, the simple slope tests demonstrated that among respondents with lower (Mean-1SD = 2.51) levels of bridging social capital, the positive association between the perceived benefits of AI and the attitude toward generative AI tools became stronger (b = 0.515, SE = 0.037, t = 14.078, p = .000, 95% CI = [0.443, 0.587]), compared with those with moderate (Mean = 2.97) levels of bridging social capital (b = 0.371, SE = 0.033, t = 11.421, p = .000, 95% CI = [0.307, 0.434]) and higher (Mean+1SD = 3.43) bridging social capital (b = 0.227, SE = 0.043, t = 5.316, p = .000, 95% CI = [0.143, 0.310]). The Johnson-Neyman test identified the moderator value of the significant region (value = 3.793, [95.960% below, 4.040% above]). In sum, this implies that those with higher bridging social capital may have relatively lower attitude toward generative AI tools even with same extent of the perceived benefits of AI as others.



Note: moderated mediation index = -0.056, 95% CI = -0.099, -0.017; *p < .05, **p < .01, ***p < .001.

Figure 3. Results of Moderated Mediation Analysis

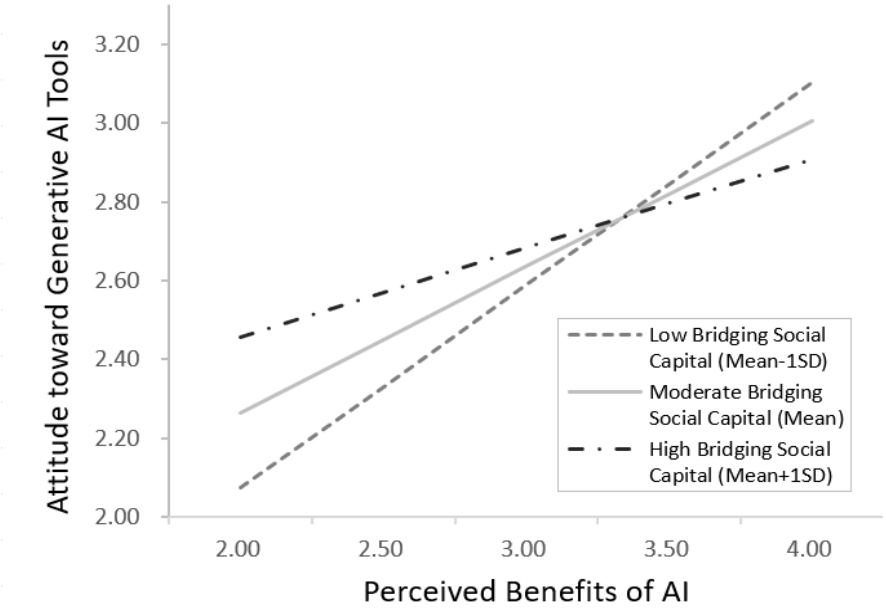


Figure 4. Results of Moderation Analysis

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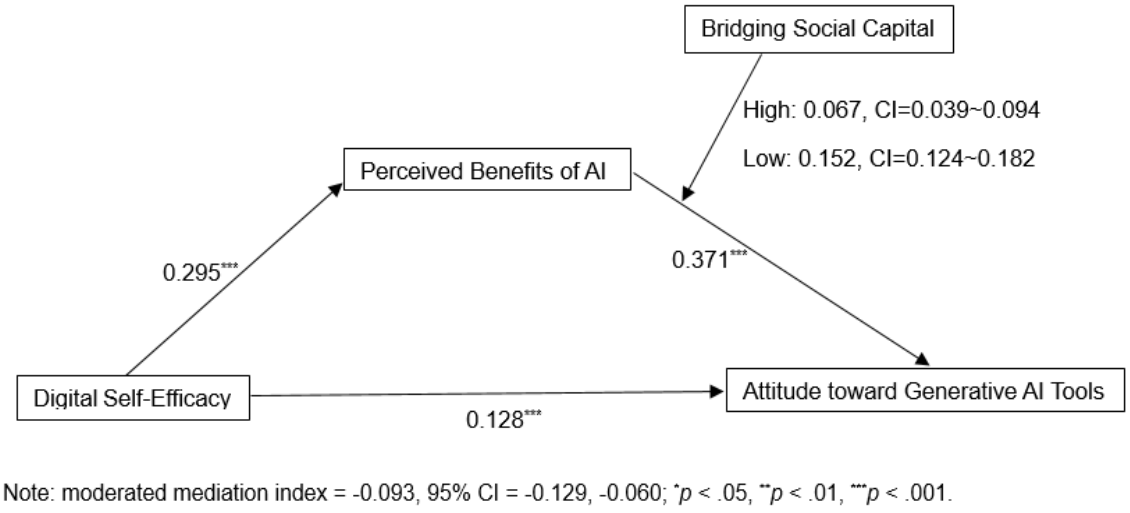
In addition to the two-way interaction, results further demonstrated a significant moderated mediation model, in which the association between digital self-efficacy and the attitude toward generative AI tools mediated through the perceived benefits of AI was further moderated by bridging social capital (Moderated Mediation Index = -0.093, Boot SE = 0.018, 95% CI = [-0.129, -0.060]). That is, the perceived benefits of AI mediate the effect of digital self-efficacy on the attitude toward generative AI tools, and this indirect effect is moderated by bridging social capital. Specifically, as shown in Figure 5, among respondents with lower (Mean-1SD) levels of bridging social capital, the indirect effect of digital self-efficacy on the attitude toward generative AI tools was significant and stronger (b = 0.152, Boot SE = 0.015, 95% CI = [0.124, 0.182]), compared with those with moderate (Mean) levels of bridging social capital (b = 0.109, Boot SE = 0.012, 95% CI = [0.086, 0.134]) and higher (Mean+1SD) levels of bridging social capital (b = 0.067, Boot SE = 0.014, 95% CI = [0.039, 0.094]). In sum, the moderated mediation effect was present both in the high and low levels of bridging social capital. In general, the finding implies that the indirect effect of digital self-efficacy on attitude toward generative AI tools, via the perceived benefits of AI, significantly decreases as bridging social capital increases from low level to high level.



Note: moderated mediation index = -0.093, 95% CI = -0.129, -0.060; *p < .05, **p < .01, ***p < .001.

Figure 5. Results of Moderated Mediation Analysis

DISCUSSION

In the current research, we explore the factors affecting the individuals' attitude toward generative AI tools such as ChatGPT, Google Gemini, and so on. Specifically, we first examine whether individuals' digital self-efficacy and perceived benefits of AI influence their attitudes toward the generative AI tools, controlling for the effects of demographic variables and prior usage experience with generative AI tools (RQ1). Second, we examine whether the digital self-efficacy affects the attitude toward the generative AI tools via the perceived benefits of AI (RQ2). Third, we examine whether the mediation effect of the perceived benefits of AI on the association between the digital self-efficacy and attitude toward the generative AI tools is moderated by bonding social capital (RQ3) and bridging social capital (RQ4), respectively; that is, we examine whether the mediation effect of the perceived benefits of AI on the association between the digital self-efficacy and attitude toward the generative AI tools is weaker at a high (vs. low) level of social capital. To answer the RQ1, a hierarchical multiple regression analysis was first performed using the Koreans who were aware of the generative AI tools. The results indicate that the digital self-efficacy as well as the perceived benefits of AI are positively associated with the attitude toward generative AI tools. Second, regarding the RQ2, we analyzed the role of perceived benefits of AI as a mediator between the digital self-efficacy and the attitude toward generative AI tools. The results reveal that the digital self-efficacy impacts the attitude toward generative AI tools via the perceived benefits of AI. Third, regarding the RQ3 and RQ4, using the moderated mediation approach, we tested whether the indirect effect of digital self-efficacy on attitude toward generative AI tools, via the perceived benefits of AI, is moderated by bonding social capital and bridging social capital, respectively. The results indicate that the indirect effect of digital self-efficacy on attitude toward generative AI tools, via the perceived benefits of AI,

significantly decreases as social capital (i.e., bonding social capital, bridging social capital) increases from low level to high level.

Although this research has some important implications for academic researchers and practitioners, it is not without limitations. Thus, we present possible research directions for future studies. First, this study solely focused on the 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 Koreans significantly improves the external validity of results, they are only generalizable within South Korea. As such, replication of this work in various countries is recommended. Second, future research could consider other various dependent variables (e.g., emotional attitude, behavioral intention, etc.), which will provide more insights into the generative AI tools. Third, future research could investigate other factors affecting the individuals' attitudes toward generative AI tools and consider other types of social capital (e.g., cognitive social capital) as a moderator.

The findings contribute to a comprehensive understanding of the factors affecting the individuals' attitudes toward generative AI tools, not only supplementing previous research but also providing a theoretical basis for systematic research on individuals' digital self-efficacy and perceptions of AI impacting their attitudes toward generative AI tools. Moreover, the research findings are expected to be of key essence to practitioners and policymakers from various fields, providing invaluable insight into enhancing the attitude toward generative AI tools. Specifically, it is necessary to increase individuals' digital self-efficacy through capitalizing online resources or policy-driven investments (e.g., online education platforms, training programs, tech communities, etc.). It is also important to widely inform people about the benefits of AI in order to make them find generative AI tools beneficial to their daily lives. In addition, it is necessary to consider that people with higher level of social capital tend to be cautious toward generative AI tools and may have difficulties in adopting new relationship with them.

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