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I Was Born to Love AI: The Influence of Social Status on AI Self-Efficacy and Intentions to Use AI

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This study employed a survey to examine the role of social status on the acceptance of artificial intelligence (AI) technology. One's self-efficacy with using AI technology was assumed to be determined by various factors coming from demographic status, which ultimately leads to the intention to use that technology. This was hypothesized based on the technology acceptance model, self-efficacy, and diffusion of innovation. Participants (n = 369) reported their perceived mastery of AI products, vicarious experiences with AI products, social persuasions of using AI products, AI self-efficacy, perceived usefulness of AI, perceived ease of using AI, intention to use AI, and demographic information. Both education level and income were found to affect the intention to adopt AI technology through AI self-efficacy. However, the age of participants was found not to be a determinant. The implications of the findings for applications and theory are discussed.

Keywords: technology acceptance model, self-efficacy, diffusion of innovation, social status, artificial intelligence

Artificial intelligence (AI) has become pervasive and changes people's lives every day. However, whenever a new technology comes out, it is not provided equivalently to people; instead, the distribution of innovative technology is varied based on individuals' socioeconomic status (Rogers, 1995). Although many various AI products are in people's lives, there are more to come. The distribution of those new AI products may follow this pattern. For instance, purchasing a vehicle with an autonomous driving system is financially more burdensome than buying a vehicle without it (Nunes & Hernandez, 2019). Therefore, AI technology is likely to be primarily distributed to people or organizations with more resources (Rasool, 2019; Wells, 2017). Thus, while it is believed that AI technology is widely diffused, it should be asked whether it is evenly distributed. Some people argue that AI technology is fairly distributed since it has permeated everyone's lives without them realizing it (Marr, 2019; Naff, 2020). It is true that many companies employ AI technology in their services, which makes their users automatically use AI technology. However, even those services or products are unevenly provided from the beginning based on people's social status, which ultimately hinders the accessibility of AI technology. People who use a smartphone are more likely to be exposed to AI technology than others since the applications they use are AI-powered, such as a spam mail filter or a navigation system. However, some people still do not have a smartphone, and they are less likely to experience AI technology than others. Therefore, people with more resources have more access to AI technology.

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These different levels of AI accessibility can later turn into a critical social issue. It has been argued that using AI technology leads to better productivity and performance (Anderson & Rainie, 2018). In other words, having no access to AI technology can result in a lack of competitiveness. This can continue as a vicious cycle in which people or organizations with more assets and capital will keep their fortunes by being more competitive than those without AI technology. Moreover, there has been a global concern that machines will replace human labor (Granulo, Fuchs, & Puntoni, 2019; Zhou, Chu, Li, & Meng, 2020). Therefore, some people will be more efficient with the help of AI technology, while others will get replaced by it. In other words, AI technology can produce more severe social polarization. So, having no intention to use AI technology, or even avoiding it, may result in a person being more socially marginalized. For instance, older adults are already rejecting new technology because they think learning it is arduous and time consuming, making them more socially isolated and unemployed (Knowles & Hanson, 2018; Lee, Czaja, & Sharit, 2008). The widening and deepening penetration of AI technology in society will intensify this issue and solidify social stratification. Therefore, studies that seek to identify the factors that affect AI technology distribution are needed. Understanding the distribution pattern of AI technology and its acceptance makes it possible to seek an alternative approach to the fair and equivalent diffusion of AI technology.

The variation in new technology distribution, based on socioeconomic factors, is expected to affect one’s confidence in using technology because there is a positive relationship between technology experiences and technology self-efficacy (Rowston, Bower, & Woodcock, 2020). Technology self-efficacy is a crucial factor in understanding innovative technology. Past studies have provided empirical data showing that people with technology self-efficacy are more likely to accept relevant technological products and services (Hsia, Chang, & Tseng, 2014; Tsai, Hung, Yu, Chen, & Yen, 2019; Yang, 2010). Therefore, this study aims to determine the relationship between socioeconomic factors and intentions to use AI technology, as well as the effect of AI self-efficacy on this relationship. Because this study is about how people adopt new technology, the technology acceptance model (TAM) is employed. Also, this study uses Bandura’s self-efficacy (1977) and Rogers’s (1995) diffusion of innovation to identify the influence of demographic status and confidence in using AI products on willingness to use AI technology.

Why Is AI Special?

Although AI is often regarded as a single technology, it is a field in science that attempts to build intelligent machines (Russell & Norvig, 2020; Walch, 2018). Many AI-based products, such as self-driving cars, social robots, and facial recognition programs, are byproducts of its development. Therefore, AI technology is an inclusive term that encompasses various subfield technologies developed to create an artificial brain. Even within machine learning, there are supervised, unsupervised, and reinforcement learning types, which are used distinctively based on the purpose of programs. In other words, items that we call AI products may actually use different technologies. So, attitudes toward a single AI product do not fully represent the public perception of AI. Therefore, researchers should use an integrative approach by examining AI technology as a whole instead of focusing on individual products.

Because of the peculiarity of AI, research on AI technology acceptance should be conducted in a different manner from other technology acceptance studies. For instance, it is possible to predict a person’s intention to purchase a new vehicle based on his or her past experiences and perceptions of cars. However, to see how an individual reacts to AI technology, the person's experience and perception of various AI products should be analyzed. This study aims to test whether theories about technology adoption—the TAM, self-efficacy, and diffusion of innovation—can explain the acceptance of AI despite its distinctiveness.

Public Perceptions of Artificial Intelligence

Despite the prevalent use of the term AI, it is defined based on the individual's interests because it is an inclusive term that consists of different technologies. For instance, scholars approach it based on its functionality, but policymakers define it with comparisons between humans and machines (Krafft, Young, Katell, Huang, & Bugingo, 2019). There was an attempt to define AI using four categories, which are acting humanly, thinking humanly, thinking rationally, and acting rationally (Russell & Norvig, 2020). Acting humanly refers to how close AI's performances are to human behaviors. It is often evaluated using the Turing test, which is used to assess the similarity between a machine's performance and a human's (Saygin, Cicekli, & Akman, 2000). Thinking humanly refers to how similar humans and machines are when processing information. The approach mainly uses cognitive modeling based on the assumption that machines should imitate the human reasoning step. Thinking rationally is about whether machines use logical processes and codified laws of thoughts. In other words, within this definition, AI is a machine that performs logical reasoning. Lastly, acting rationally sees AI as a rational machine agent with long-period autonomous performances using its ability to perceive and adapt to surroundings. This approach claims that AI can always find the optimal answers with its rational reasoning. It should be noted that these four approaches to defining AI are not mutually exclusive.

However, individuals' attitudes toward the use of technology may not be determined by their technical knowledge. For instance, people often use technology devices without having expert understanding of how they work. Also, they understand AI technology based on their experiences with it. It was, in fact, found that the attitudes toward AI are influenced by socioeconomic status; young, wealthy, educated, liberal males with more experience with technology are more likely to have more AI preferences than others (Zhang & Dafoe, 2019). The study suggested considering people's social circumstances and socioeconomic factors when examining their attitudes toward AI. It is presumed that these personal understandings of AI coming from different social backgrounds affect intentions to use AI technologies since subjective norms are prerequisites of behavioral intention (Fishbein & Ajzen, 1975). Because people's understanding of AI largely relies on their AI product usage, this study asks their perceptions based on widely used AI items that prior researchers deemed AI-enabled devices, not based on the scientific concept.

Technology Acceptance Model

The TAM is a theoretical framework that explains how people adopt and use technology (Davis, Bargozzi, & Warshaw, 1989). TAM is a theory developed from the theory of reasoned action (TRA), which claims that behaviors are the product of preexisting attitudes and subjective norms (Fishbein & Ajzen, 1975). According to TAM, behaviors can be predicted by understanding the motivations behind them (Sheppard, Hartwick, & Warshaw, 1988). Aligning with the argument of TRA, TAM identifies the motivations for using new technology and argues that perceived usefulness (PU) and perceived ease of use (PEOU) are the primary motivators (Davis, 1989). Both PEOU and PU increase behavioral intentions to use a technology, which is the dependent variable of this model (Venkatesh & Davis, 2000). Therefore, the primary purpose of TAM studies is to find external variables that influence PEOU and PU.

Being a robust model, TAM has shown its applicability in many areas (King & He, 2006), and the acceptance of AI, such as in an automated recommendation system or self-driving cars, is one of them (Koul & Eydgahi, 2018; Lee, Ahn, & Han, 2007; Shih et al., 2011; Wong et al., 2012). Since the purpose of this research is also to inquire about the prerequisites of accepting AI, it considers TAM. However, most past TAM studies have focused on the intention to use a single AI product or service, such as a chatbot or a social robot, not AI technology in general. For instance, there may be cases in which people might prefer to use a particular AI product, such as a smart home device, but have concerns about society using AI technology too much. Whether or not positive attitudes coming from experiences with AI products lead to the intention to keep using AI technology overall has not been tested, which is the aim of this study.

H1a: Perceived ease of using AI has a positive relationship with perceived usefulness of AI.

H1b: Perceived ease of using AI has a positive relationship with the intention to use AI technology.

H1c: Perceived usefulness of AI has a positive relationship with the intention to use AI technology.

AI Self-Efficacy

According to Bandura (1994), self-efficacy is a belief about one's own ability to produce desired goals. In other words, it is a feeling of competency to fulfill the desired goal. It means that people with high perceived self-efficacy are more likely to believe they can successfully perform given tasks. People with lower self-efficacy tend to perceive the required task to be more complicated compared to people with higher self-efficacy (Hasan, 2007). So, people with higher self-efficacy are found to show higher performance accomplishments and lower emotional arousal (Bandura, 1982). For instance, people with lower self-efficacy with AI technology will see using AI products, such as self-driving cars or smart assistants, as more complicated and stressful, which leads them to be less likely to use those items.

Based on social cognitive theory, which argues that people learn by observing others, self-efficacy is seen as a determinant of behaviors (Bandura, 1988). Also shown to increase self-efficacy are performance accomplishments, which refer to a person's perceived level of mastery and vicarious experiences, or having confidence by seeing other people succeed (Bandura, 1977). Multiple empirical studies in various fields have found that prior vicarious and personal experiences in using a technology strengthen a person's level of self-efficacy (Bartsch, Case, & Meerman, 2012; Hodges & Murphy, 2009). Therefore, people who either have perceived mastery of AI technologies or know people with AI product proficiencies are expected to have more AI self-efficacy than people with neither of them. Also, social persuasion, having encouragement from others about completing a task, is found to increase self-efficacy, which leads to putting more effort into their tasks (Bandura, 1977). Therefore, people who are encouraged to use AI devices from others are more likely to have higher AI self-efficacy.

Technology self-efficacy refers to the belief in one's capacity to use technology for pursuing benefits (Holden & Rada, 2011; Wang, Shannon, & Ross, 2013). Therefore, people with high technology self-efficacy are more confident in using technology. With an integrative approach to self-efficacy and the TAM, high self-efficacy leads to the perception that technology is more useful and easier to use (Lee et al., 2007; Surendran, 2013). Multiple empirical studies have shown that people with more technology self-efficacy feel that technology embodies higher PEOU and usefulness (Faqih, 2013; Mun & Hwang, 2003; Wangpipatwong, Chutimaskul, & Papasratorn, 2008). It is expected that AI will follow the same acceptance pattern those previous technologies have shown. Therefore, having more AI self-efficacy will enhance the perception of AI as being more useful and easier to use. These are the hypotheses based on the idea:

H2a: *More perceived mastery of using AI products leads to higher AI self-efficacy.*

H2b: *More vicarious experiences in using AI products lead to higher AI self-efficacy.*

H2c: *More social persuasions of using AI products lead to higher AI self-efficacy.*

H2d: *AI self-efficacy has a positive relationship with the perceived ease of using AI.*

H2e: *AI self-efficacy has a positive relationship with the perceived usefulness of AI.*

RQ1: *Would technology acceptance variables (perceived ease of using AI and perceived usefulness of AI) mediate the relationship between AI self-efficacy and the intention to use AI technology?*

Diffusion of Innovation

As mentioned earlier, there is a socioeconomic variation in accepting technological innovations, which diffusion of innovation (DoI) claims (Rogers, 1995). According to Rogers (1995), adopters are categorized into five groups: (a) innovator, (b) early adopters, (c) early majority, (d) late majority, and (e) laggards (listed in order from earliest to latest). Although the distinction was claimed to be based on innovativeness, it was, in fact, highly influenced by socioeconomic factors. Rogers wrote that early adopters tend to have more years of education, higher social status, more financial and social resources, and greater upward social mobility than late adopters. Although there is no clear causal relationship between socioeconomic factors and innovativeness, Rogers claims that innovators can afford to be venturous, as they have enough resources to overcome losses from wrong decisions. Similarly, Shipps (2013) also found that socioeconomic factors are directly related to the adoption of new technologies. Therefore, socioeconomic factors, which are annual income and educational level, are expected to influence people's AI self-efficacy.

While Rogers (1995) found no significant result about the innovation diffusions in terms of age, there have been previous DoI studies that considered the age group of participants (van Rijnsoever & Donders, 2009; Zhou, 2008; Zhu & Zhang, 2016). It is because older populations are thought to be more reluctant to adopt technological innovations and think themselves too old to learn new things (Chung, Park, Wang, Fulk, & McLaughlin, 2010; Niehaves & Plattfaut, 2014; Turner, Turner, & Van de Walle, 2007).

Furthermore, the effect of age differences on the attitudes toward AI products has already been confirmed in previous studies, such as in self-driving cars and robots (Lee, Ward, Raue, D'Ambrosio, & Coughlin, 2017; Martínez-Miranda, Pérez-Espinosa, Espinosa-Curiel, Avila-George, & Rodríguez-Jacobo, 2018). Therefore, the study includes the age of the participants as another socioeconomic factor. Overall, the education level, age, and social class of participants are considered in this study.

H3a: The education level has a positive relationship with perceived mastery of using AI products.

H3b: The education level has a positive relationship with vicarious experiences of using AI products.

H3c: The education level has a positive relationship with social persuasions of using AI products.

H4a: The year of birth has a positive relationship with perceived mastery of using AI products.

H4b: The year of birth has a positive relationship with vicarious experiences of using AI products.

H4c: The year of birth has a positive relationship with social persuasions of using AI products.

H5a: The annual income has a positive relationship with perceived mastery of using AI products.

H5b: The annual income has a positive relationship with vicarious experiences of using AI products.

H5c: The annual income has a positive relationship with social persuasions of using AI products.

RQ2: Would self-efficacy variables (perceived mastery, vicarious experience, and social persuasion) mediate the relationship between social-status factors (education level, age, and annual income) and AI self-efficacy?

RQ3: Would AI self-efficacy mediate the relationship between self-efficacy variables (perceived mastery, vicarious experience, and social persuasion) and technology-acceptance variables (perceived ease of using AI and perceived usefulness of AI)?

Methods

Procedures

A sample size for the current U.S. population (*N* = 332,915,074) with 95% confidence level and 5% margin of error was calculated using Qualtrics' sample size calculator (https://www.qualtrics.com/blog/calculating-sample-size/). Although 385 was the ideal sample size, 603 participants were recruited from Amazon Mechanical Turk (MTurk) for participation in an online survey considering the number of participants who may not pass attention-checking questions. On average, the survey took about 9.25 minutes, and $0.50 was provided as compensation for participation. Two attention-checking questions (i.e., choose an item that was NOT mentioned in the reading; I am answering questions randomly) were asked of those who agreed to participate, and people who failed were excluded, leaving 369 participants. The youngest participant was 19 years old, and the oldest was 73 years old (M = 36.49, SD = 11.19). In terms of gender, 62.3% of them identified as male, 37.4% of them identified as female, and 0.03% identified as nonbinary. They were asked to report their perceived mastery of AI products, vicarious experiences with AI products, social persuasions of using AI products, AI self-efficacy, PU of AI, PEOU AI, intention to use AI, and demographic information. This study was reviewed by the University of Southern California Institutional Review Board (IRB) and determined to be exempt (UP-20-00934).

Measures

Perceived Mastery of AI Products

The level of AI product experiences was measured by asking participants how comfortable they were with various types of commercialized AI products that are easily accessible. Since people may have different understandings of what AI products are, a list of AI products was given. The products are (1) email spam filters, (2) smart replies in Gmail, (3) chatbots, (4) Google's predictive searches, (5) product recommendations, (6) music recommendations, (7) ride-sharing apps, (8) Google Maps navigation, (9) facial recognition in smartphones, (10) digital voice assistance, (11) smart home devices, and (12) video recommendations. The items were chosen from AI products that are reported to be used in everyday life (Bradley, 2018; Marr, 2019; see appendix). The following questions were asked with a seven-point Likert scale (from "strongly disagree" to "strongly agree"): (a) Are you comfortable with using these items? (b) Are you confident using these items? (c) Are you proficient in using these items? Higher scores indicate more experience with AI products (α = .80).

Vicarious Experiences with AI Products

Vicarious experiences with AI products indicate how much participants think other people around them are proficient with AI products. The only difference with perceived mastery of AI products is that the perception of other people's mastery level with AI products was asked, not theirs. With a seven-point Likert scale (from "strongly disagree" to "strongly agree"), the scale asked the following questions: When thinking of people who are close to you, (a) are they comfortable with using these items? (b) are they confident using these items? (c) do they usually need the help of others to use these items? and (d) are they proficient in using these items? The same AI products mentioned above were shown. Higher scores indicate that others have more experience with AI products (α = .80).

Social Persuasions

Social persuasions describe the encouragement participants receive from the people around them. To measure this, a four-item scale revised from the social influence scale (Robinson Jr., 2006) was used, which consists of the following statements: (a) People who influence my behavior think I should use AI technology; (b) People who are important to me think I should use AI technology; (c) People around me have been helpful in the use of AI technology; and (d) People around me have supported the use of AI technology. The scale used a seven-point Likert scale (from "strongly disagree" to "strongly agree"). Higher scores indicate greater social persuasions from others to use AI technologies (α = .80).

AI Self-Efficacy

To measure confidence in using AI technologies, a revised technology self-efficacy scale (Holden & Rada, 2011) was used. The scale asks: In general, I could complete any desired task using the AI technology if (a) there was no one around to tell me what to do as I go; (b) I had never used technology like it before; (c) I had only the manuals for reference; (d) I had seen someone else using it before trying it myself; (e) I could call someone for help if I get stuck; (f) someone else helped me get started; (g) I had a lot of time to complete the task for which the technology was provided; (h) I had just the built-in help facility for assistance; (i) someone showed me how to do it first; and (j) I had used similar technologies before this one to do the same task. It used a seven-point Likert scale (from "strongly disagree" to "strongly agree"). Higher scores indicate greater efficacy when using AI technologies (α = .87).

Perceived Usefulness of AI

The PU of AI was measured using a previously devised nine-item scale (Holden & Rada, 2011). The scale measures performance, productivity, effectiveness, usefulness, relevance, and output quality when using AI technology. It used a seven-point Likert scale (from "strongly disagree" to "strongly agree"). Higher scores indicate higher perceived ease of using AI (α = .85).

Perceived Ease of Using AI

Perceived ease of using AI was measured using a six-item scale (Holden & Rada, 2011). The scale measures the understandability, required mental effort, ease of use, flexibility, learnability, memorability, navigation, and functionality of using AI technologies. The scale used a seven-point Likert scale (from "strongly disagree" to "strongly agree"). Higher scores indicate a higher PU of AI (α = .87).

Intention to Use AI

How much participants intend to adopt overall AI technology was measured using a scale for attitudes toward using technology (Holden & Rada, 2011). The scale asks how much using AI-powered technologies is (a) good or bad, (b) wise or foolish, (c) favorable or unfavorable, (d) beneficial or harmful, and (e) positive or negative, using a seven-point binary variable scale. Higher scores indicate having more intention to use AI products (α = .90).

Demographic Information

Participants were asked to disclose their demographic information, including their ages, ethnicities, annual income, and levels of education.

Results

Findings in terms of the correlation matrix for the variables are shown in Table 1. As shown in Table 1, variables related to the TAM, AI self-efficacy, and diffusion of innovation showed positive and significant correlations with each other. Also, the education level was positively and significantly correlated only with social persuasions. Additionally, annual income showed positive and significant correlations with perceived mastery of AI products, social persuasions, AI self-efficacy, PU of AI, PEOU AI, intention to use AI, and the education level. Participants' ages showed no correlation with other variables.

Table 1. Correlations Between Study Variables.

Item	1	2	3	4	5	6	7	8	9	10
Perceived mastery of AI products	1									
Vicarious experiences with AI products	.65**	1								
Social persuasions	.47**	.55**	1							
AI self-efficacy	.54**	.48**	.32**	1						
Perceived usefulness of AI	.55**	.47**	.56**	.47**	1					
Perceived ease of using AI	.67**	.60**	.54**	.63**	.69**	1				
Intention to use AI	.49**	.39**	.35**	.36**	.53**	.52**	1			
Age	.06	−.03	.00	−.02	.02	.05	−.01	1		
Education	.07	.08	.12*	−.03	.09	.10	−.05	−.04	1	
Annual income	.20**	.09	.13*	.16**	.25**	.19**	.15**	−.06	.18**	1

Note. n = 369. ** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

A simple linear regression was conducted to test *H1a* that predicted a positive relationship between the PEOU AI and the PU of AI. Also, a multiple linear regression was conducted to test *H1b* that predicted a positive relationship between the PEOU AI and the intention to use AI technology, and *H1c* that predicted a positive relationship between the PU of AI and the intention to use AI technology. A significant and positive effect was found between the PEOU AI and the PU of AI [$F(1, 367) = 333.61$, $p < .001$], with $r^2 = 0.48$. The intention to use AI technology showed a significant and positive relationship with the PEOU AI and the PU of AI [$F(2, 366) = 87.78$, $p < .001$], with $r^2 = 0.32$. Table 2 shows the regression analysis results in detail. Based on the results, *H1a*, *H1b*, and *H1c* were all supported.

Table 2. Hypotheses 1 Regression Analysis Summary.

Hypothesis	IV	DV	*B*	95% CI	*β*	*T*	*p*
	(Constant)	Perceived	1.37	[1.13, 1.61]		5.75	<.001
H1a	Perceived Ease of Use	Usefulness	0.77	[0.72, 0.81]	.69	18.27	<.001
	(Constant)	Intention to	0.85	[0.47, 1.23]		20.48	.026
H1b	Perceived Ease of Use	Use AI	0.45	[0.37, 0.53]	.33	5.60	<.001
H1c	Perceived Usefulness		0.43	[0.34, 0.51]	.29	4.82	<.001

Note. IV = independent variable, DV = dependent variable.

Another multiple linear regression was conducted to see the relationship of AI self-efficacy with perceived mastery of using AI products (*H2a*), vicarious experiences in using AI products (*H2b*), and social persuasions of using AI products (*H2c*), [$F(3, 365) = 56.65$, $p < 0.001$], with $r^2 = 0.32$. While perceived mastery and vicarious experiences in using AI products showed significant relationships with AI self-efficacy, social persuasions did not. *H2d* predicted a positive relationship between AI self-efficacy and the perceived ease of using AI. A significant and positive effect was found [$F(1, 367) = 103.58$, $p < .001$], with $r^2 = 0.22$. *H2e* argued that there is a positive relationship between AI self-efficacy and the PU of AI. A significant and positive effect was found [$F(1, 367) = 235.97$, $p < .001$] with $r^2 = 0.39$. Therefore, *H2a*, *H2b*, *H2d*, and *H2e* were supported, but not *H2c*. Table 3 shows the regression analysis results in detail.

Table 3. Hypotheses 2 Regression Analysis Summary.

Hypothesis	IV	DV	B	95% CI	β	*T*	*p*
	(Constant)	AI self-Efficacy	2.07	[1.79, 2.35]		7.42	<.001
H2a	Perceived mastery		0.37	[0.31, 0.42]	.38	6.60	<.001
H2b	Vicarious experiences		0.21	[0.15, 0.27]	.22	3.54	<.001
H2c	Social Persuasion		0.02	[−0.02, 0.07]	.03	0.47	.64
H2d	(Constant)	Perceived Ease of Use	1.83	[1.59, 2.08]		7.48	<.001
	AI self-Efficacy		0.66	[0.62, 0.70]	.63	15.36	<.001
H2e	(Constant)	Perceived Usefulness	3.02	[2.77, 3.27]		11.95	<.001
	AI self-Efficacy		0.45	[0.40, 0.49]	.47	10.18	<.001

Note. IV = independent variable, DV = dependent variable.

To test RQ1, which asks whether perceived ease of using AI and PU of AI mediate the relationship between AI self-efficacy and the intention to use AI technology, the SPSS PROCESS Macro Model 4 was used with 95% bias-corrected bootstrap confidence intervals (Cis, with 5,000 bootstrap samples; Hayes, 2018). The results confirmed that both perceived ease of using AI ($b = 0.42$, BCa CI [0.32, 0.54]) and PU of AI ($b = 0.31$, BCa CI [0.22, 0.41]) showed a significant indirect effect since there was no 0 between their lower and upper levels of CI interval (Shrout & Bolger, 2002).

Another set of linear regressions was conducted to test *H3a*, *H3b*, and *H3c*, which claimed that education level has a positive relationship with perceived mastery of using AI products, vicarious experiences of using AI products, and social persuasions of using AI products. It was found that perceived mastery of using AI products [$F(1, 367) = 2.03$, $p = .16$, $r^2 = 0.01$] and vicarious experiences of using AI products [$F(1, 367) = 2.16$, $p = .14$, $r^2 = 0.01$] had an insignificant relationship with education level. Therefore, *H3a* and *H3b* were rejected. However, a significant relationship was found between the education level and social persuasions of using AI products [$F(1, 367) = 5.57$, $p = .02$, $r^2 = 0.02$], which showed that *H3c* was supported. Table 4 shows the regression analysis results in detail.

Table 4. Hypotheses 3 Regression Analysis Summary.

Hypothesis	IV	DV	*B*	95% CI	*β*	*t*	*p*
H3a	(Constant)	Perceived mastery	5.47	[5.19, 5.75]		19.41	<.001
	Education level		0.13	[0.04, 0.21]	.07	1.43	.16
H3b	(Constant)	Vicarious experiences	5.34	[5.07, 5.62]		19.48	<.001
	Education level		0.13	[0.04, 0.21]	.08	1.47	.14
H3c	(Constant)	Social persuasion	4.78	[4.48, 5.09]		15.68	<.001
	Education level		0.23	[0.13, 0.32]	.12	2.36	.02

Note. IV = independent variable, DV = dependent variable.

H4a, *H4b*, and *H4c* argued that the year of birth has a positive relationship with perceived mastery of using AI products, vicarious experiences of using AI products, and social persuasions of using AI products. Results from simple linear regressions showed that age had an insignificant relationship with perceived mastery of using AI products [$F(1, 367) = 1.11$, $p = .29$, $r^2 = 0.00$], vicarious experiences of using AI products [$F(1, 367) = 0.44$, $p = .51$, $r^2 = 0.00$], and social persuasions of using AI products [$F(1, 367) = 0.02$, $p = .90$, $r^2 < 0.001$]. Table 5 shows the regression analysis results in detail. Based on the results, *H4a*, *H4b*, and *H4c* were rejected.

Table 5. Hypotheses 4 Regression Analysis Summary.

Hypothesis	IV	DV	*B*	95% CI	*β*	*t*	*p*
H4a	(Constant)	Perceived mastery	−2.36	[−10.18, 5.47]		−0.30	.76
	Age		0.00	[0.00, 0.01]	.06	1.05	.29
H4b	(Constant)	Vicarious experiences	10.78	[3.17, 18.40]		1.42	.16
	Age		−0.00	[−0.01, 0.00]	−.04	−0.66	.51
H4c	(Constant)	Social persuasion	4.44	[−4.07, 12.96]		0.52	.60
	Age		0.00	[−0.00, 0.01]	.01	0.12	.90

Note. IV = independent variable, DV = dependent variable.

H5a, *H5b*, and *H5c* claimed that the annual income has a positive relationship with the perceived mastery of using AI products, vicarious experiences of using AI products, and social persuasions of using AI products. While vicarious experiences of using AI products showed an insignificant outcome [$F(1, 367) =$

2.90, p = .09, r^2 = 0.01], perceived mastery of using AI products [F(1, 367) = 14.69, p < 0.001, r^2 = 0.04] and social persuasions of using AI products [F(1, 367) = 6.28, p = .013, r^2 = 0.02] had significant relationships with the annual income. Therefore, *H5a* and *H5c* were supported, while *H5b* was not. Table 6 shows the regression analysis results in detail.

Table 6. Hypotheses 5 Regression Analysis Summary.

Hypothesis	IV	DV	*B*	95% CI	*β*	*t*	*p*
H5a	(Constant)	Perceived	5.58	[5.49, 5.66]		63.64	<.001
	Annual income	mastery	0.08	[0.61, 0.11]	.20	3.83	<.001
H5b	(Constant)	Vicarious	5.61	[5.53, 5.70]		64.08	<.001
	Annual income	experiences	0.04	[0.02, 0.06]	.09	1.70	.09
H5c	(Constant)	Social	5.28	[5.19, 5.38]		54.85	<.001
	Annual income	persuasion	0.06	[0.04, 0.08]	.13	2.51	.013

Note. IV = independent variable, DV = dependent variable.

RQ2 was about whether AI self-efficacy variables mediate the relationship between social status factors and AI self-efficacy. Because *H3c*, *H5a*, and *H5c* were supported, the relationships with variables only from those hypotheses were examined. The same SPSS PROCESS Macro Model 4 with 95% bias-corrected bootstrap CIs (and 5,000 bootstrap samples) was used (Hayes, 2018). Education level had a significant indirect effect on self-efficacy through social persuasions to use AI, b = 0.065, BCa CI [0.008, 0.135]. Annual income was also found to have significant indirect effects on self-efficacy through perceived mastery of AI product use (b = 0.041, BCa CI [0.023, 0.061]) and social persuasions to use AI (b = 0.016, BCa CI [0.002, 0.034]).

Finally, *RQ3* about AI self-efficacy mediation of the link between self-efficacy variables and technology acceptance variables was tested using the same SPSS PROCESS Macro Model 4 with 95% bias-corrected bootstrap CIs (with 5,000 bootstrap samples) (Hayes, 2018). Perceived mastery had a significant indirect effect on both PU (b = 0.131, BCa CI [0.066, 0.210]) and perceived ease of using AI products (b = 0.182, BCa CI [0.122, 0.261]) through AI self-efficacy. Also, the results showed a significant indirect effect of vicarious experiences on both the PU (b = 0.155, BCa CI [0.091, 0.234]) and perceived ease of using AI products (b = 0.195, BCa CI [0.128, 0.276]) through AI self-efficacy. Moreover, social persuasions had a significant indirect effect on both PU (b = 0.096, BCa CI [0.050, 0.156]) and perceived ease of using AI products (b = 0.135, BCa CI [0.079, 0.201]) through AI self-efficacy.

Discussion

This study aimed to examine the influence of demographic information on AI self-efficacy and, ultimately, the intention to use AI technology. The role of variables from TAM and those related to technology self-efficacy were also examined. The results suggest a significant correlation between AI self-efficacy and a belief that using AI is easy and useful. People with more positive attitudes toward the ease of use and usefulness of AI tend to have more intentions to use AI. Also, some demographic factors are found to increase individuals' AI self-efficacy. Higher annual income increases the level of AI self-efficacy through both perceived mastery and social persuasions toward using AI products. People with more wealth have more people close to them recommending that they use AI products and are more likely to believe that they have enough experience with those items. On the other hand, the level of education was found to have a positive relationship with AI self-efficacy only through social persuasion. This means that people with higher education levels are more likely to receive advice about using AI technology, but they do not feel confident using those products. However, the difference between education and income levels is not because of an economic reason since the products introduced in the study were either free or low-priced. Indeed, it is assumed to be a cognitive reason, such as having different standards for technology mastery. This study calls for future research to test this assumption. The age of participants had no significant relationship with any variables related to AI self-efficacy. In other words, various conditions for AI self-efficacy are similarly given regardless of one's age. People are never too old to have AI self-efficacy. Finally, none of the demographic factors showed a significant relationship with vicarious experiences of using AI technology.

Moreover, this study found that people with higher AI self-efficacy were more likely to adopt AI technology since they were more likely to perceive AI as having high usefulness and ease of use, which proves a positive relationship between technology self-efficacy and technology acceptance. Also, the present study suggests that the relationship is applicable in the context of AI technology adoption. AI possesses distinctive aspects compared with other types of technology, being both anthropomorphic and autonomous (Kugurakova, Talanov, Manakhov, & Ivanov, 2015; Russell & Norvig, 2020). However, it is found that the cognitive process for AI adoption is similar to the adoption of other types of technology. In other words, the pattern of adopting technology remains similar regardless of the style and characteristics of the technology. The findings broaden the applicability of the connection between TAM and technology self-efficacy.

This study has a few limitations and suggestions for future studies. First, the annual income was the only measurement for socioeconomic status. However, the income solely might not correctly identify an individual's socioeconomic status. For instance, there may be people who retired but saved a great deal of money. Using a multifaceted approach may allow for a better explanation of the role of socioeconomic status. Also, this study showed AI products that are currently widely distributed with which people are familiar. However, showing other types of AI products, such as items that are not exposed to the public or are expensive, may induce different reactions. Future studies should consider using the type of AI items to test the influence of demographic factors on the intention to use AI technology. Moreover, this study used linear regressions and mediating effect analyses, not the structural equation model (SEM). Because this study is an exploratory one, it attempts to connect different theories one-by-one like building blocks, not testing the overall model based on a single clearly defined theory and comparing it with other possible models. Also, this study aimed to see relationships between variables that are clearly measured, not latent variables. However, since this study hints at a model integrating DoI, self-efficacy, and TAM, future studies using SEM are expected to confirm and develop the model. Finally, while this study aims to see attitudes toward AI in general, there is a possibility that examples given in the questions might have limited the scope of participants' mental image of AI. Therefore, the findings of this study may apply better to research about AI technology in everyday life. However, based on a previous finding that more proficiencies and experiences with a software program leads to general computer self-efficacy (Hasan, 2003), it is anticipated that the relationship between the perceived mastery of the given AI products and the general AI self-efficacy is still valid.

The study results have theoretical implications, namely the integration of the TAM, self-efficacy, and diffusion of innovation. The findings of this study may not seem clearly distinctive compared with the previous studies when examining them respectively based on each theory. However, the purpose of this study is to provide a synthetical perspective toward the theories. While there were studies that considered TAM and self-efficacy together (Lee et al., 2007; Surendran, 2013; Wangpipatwong et al., 2008), no study so far has included diffusion of innovation by considering socioeconomic factors. Therefore, the present study is the first to examine why people with more resources are more likely to accept new technology. The findings can also be seen as an extension of diffusion of innovation. Rogers (1995) argued that there is no causal relationship between socioeconomic factors, assuming that people with higher socioeconomic status adopt new technologies earlier than others because they can financially afford it. However, as mentioned earlier, most items shown in the study were provided for free, so having more resources does not adequately explain why people with higher socioeconomic status use new technology earlier than others. The findings of this study make a theoretical contribution by claiming that technology self-efficacy is the missing link. While this study tested the theoretical integration based on AI, it can also be applicable to other types of technology. Despite their theoretical synergy, using those theories together has not been strongly suggested. This study urges the consolidated use of those three theories to explain the social inequality of technology adoptions better. Also, the current study confirms that those theories are applicable to explain the adoption of AI despite its peculiarity that multiple technologies should be considered. However, it should be noted that this study does not make causal claims as it focused on correlations between variables through surveys. Therefore, this study suggests future research to test this integration of theories using different kinds of technology adoptions and rigorous methods to test causal relationships.

Also, the results of this study raise an essential question: How can we diminish the variations in levels of intention to use AI between social classes? While this study confirmed the indirect relationship between socioeconomic factors and the intention to use AI technology, it is not the only finding of this study. The results also point out that AI-self efficacy is a link between socioeconomic factors and the intention to use AI technology. In other words, the intention to use AI technology can be controlled by manipulating the level of AI self-efficacy. In natural circumstances, people with more resources and education are more likely to have AI technology experiences, leading to higher AI self-efficacy. However, people with lower income or less education can still have AI self-efficacy if enough opportunities to experience AI technology are offered. One way to achieve this is by providing more AI experiences and knowledge to the public, such as teaching AI during compulsory education. Fortunately, schools that teach how to use and build AI have started to emerge globally (Ark, 2020; Balaganur, 2020; Kang, 2019). This education opportunity should also be provided to marginalized people, such as elderly and low-income groups, to facilitate independent and prosperous living (Lee et al., 2008; Vaportzis, Giatsi Clausen, & Gow, 2017). Efforts from government agencies and policymakers are needed to lessen the gap in AI self-efficacy between social classes.

There have been many studies about how people use AI technology, such as interacting with AI agents (Shank, Graves, Gott, Gamez, & Rodriguez, 2019; Suen, Chen, & Lu, 2019). However, not many researchers have focused on factors that lead people to use AI technology, especially socioeconomic variables. The present study showed that certain populations are more likely to feel the need to use AI technology, which may result in inequivalent distribution. Because the lopsided distribution of AI can lead to a stronger stratification of social classes, more studies are necessary to find ways for people to use AI technology to overcome social inequality rather than strengthen it. Future research findings may reveal new ways to prevent unequal diffusion of AI technology and make it more widely accessible for social good. Therefore, this study calls for further research about how AI technology is disseminated to people; hopefully, the present study can contribute to this effort as a stepping-stone for future studies.

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