The Effect of AI Engagement on Generative AI Adoption

Triparna de Vreede
University of South Florida
tdevreede@usf.edu

Vivek Kumar Singh
University of Missouri – St. Louis
vsingh@umsl.edu

GJ de Vreede
University of South Florida
gdevreede@usf.edu

Paul Spector
University of South Florida
pspector@usf.edu

Abstract

Artificial Intelligence (AI) technology is developing at an unprecedented rate. For organizations to reap the benefits of AI, their workforce need to embrace them and adopt them into their work practices. Using Social Cognitive Theory as a theoretical lens, we examine how users' engagement with AI technologies influences their intention to use them. To this end, we adopt a multi-dimensional perspective on AI engagement and also explore how AI familiarity relates to users' engagement. We find support for the positive association between AI familiarity and AI engagement as well as between AI engagement and Intention to use.

Keywords: Generative AI, AI adoption, AI engagement, AI familiarity. Social Cognitive Theory.

1. Introduction

The integration of Artificial Intelligence (AI) into the fabric of human life has been one of the most transformative technological shifts of the past decade. This influence extends far beyond specialized domains such as healthcare, transportation, or finance, and has permeated everyday activities and decision-making processes (Littman et al., 2022). Whether it is the AI algorithms that curate our social media feeds, the virtual assistants that help manage our schedules, or the machine learning models that personalize our online shopping experiences, AI technologies are becoming increasingly interwoven into our daily routines (Wang & Preininger, 2019)

This widespread adoption is not solely a byproduct of technological advancements but is also significantly influenced by the level of user engagement with these AI systems. As computational capabilities continue to evolve, the scope of AI applications that can meaningfully enhance various aspects of human life has expanded dramatically (Littman et al., 2022). For example, AI-driven health monitoring systems are now capable of providing real-time analytics and predictive insights, thereby empowering individuals to take proactive steps in managing their health Similarly, AI-based educational platforms are revolutionizing the way we learn by offering personalized curricula and real-time feedback (Tawafak, Malik, et al., 2021).

However, despite the ubiquity of AI technologies and their potential benefits, there remains a significant gap in our understanding of how user engagement influences the adoption and sustained utilization of these systems. While some research has delved into this relationship in the context of specific applications—such as mobile banking(Hepola et al., 2020) (Hepola et al., 2020)—a comprehensive, cross-domain understanding is conspicuously absent. This is a critical oversight, given that the mechanisms driving engagement and subsequent adoption may vary significantly depending on the nature of the AI application and the specific user needs it addresses.

Moreover, the concept of user engagement itself is multi-faceted, encompassing cognitive, emotional, and behavioral dimensions. Each of these facets can have a distinct impact on a user's intention to adopt and continue using an AI system. For instance, cognitive engagement might be influenced by the perceived utility and ease of use of the AI tool, emotional engagement could be shaped by the user's trust and comfort level with the technology, and behavioral engagement may be determined by the frequency and depth of interaction with the AI system.

Given the far-reaching implications of AI technologies and the pivotal role of user engagement in their adoption, it is imperative to adopt a holistic approach to understanding this dynamic. This necessitates a shift from examining AI adoption in isolated contexts to a more systemic evaluation that accounts for the complexities and nuances of human-AI interaction. Therefore, the central research question that this paper seeks to address is: *what is the influence*

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of users' engagement with AI on their adoption intentions?

The exploration of engagement within the AI context represents a distinct avenue of research with implications that diverge considerably from traditional Information Systems (IS) contexts. AI presents a unique domain where human and machine intelligence converge, requiring us to understand how such collaborations affect employee engagement prior to rolling it out in organizations. In addition, given the increasing influence of AI in decision-making processes, understanding engagement in this context is vital for ensuring that the technology is designed and implemented in ways that foster, rather than inhibit, creativity, productivity, and agency among its users.

The study of engagement in AI contexts reveals some unique aspects that are not typically highlighted in general IS contexts. For instance, while traditional IS engagement focuses heavily on utility and efficiency, interactional AI systems like conversational agents can elicit emotional engagement among its users. In addition, the capability of AI systems to predict and adapt may result in its crossing of ethical boundaries, affecting user engagement and trust. Also, AI systems can handle complex tasks, potentially reducing cognitive load for users, which in turn could influence engagement metrics. This intimate understanding of the AI-Human relationships allows us to design systems that improve, rather than detract from, employee well-being. Therefore, investigating the complexities of engagement in AI contexts is crucial, both for advancing theoretical understanding and for guiding ethical and effective technology design in organizations.

The remainder of this paper is structured as follows. In the next section, we discuss engagement with AI. Then we discuss Social Cognitive Theory (SCT) as the theoretical lens for our study. Following that, we use the SCT lens to explain the relationships between AI familiarity and engagement as well as Engagement and intention to use AI. Then we provide the details of our method and report on our results. Finally, we discuss our findings, contributions, limitations, and directions for future research.

2. Background and Hypotheses

2.1 Engagement

Engagement is an important motivational phenomenon that can drive behavior and performance in a variety of IS and non-IS contexts (Alessandri et al., 2015; Rashid & Asghar, 2016). It refers to an individual's state of being occupied with an activity in a manner that displays energy, involvement, and efficacy (Maslach & Leiter, 1997). Engagement is an important component of most human-IS interactions that are goal-driven and behavior focused, such as online learning, gaming, shopping, social media use, crowdsourcing, and citizen science (Chan & Pan, 2008; Cresswell et al., 2013; Kim & Baek, 2018; Liu et al., 2017; McLean, 2018; Ray et al., 2014; Roshan et al., 2019). Higher levels of engagement are related to greater performance at work (Schaufeli, 2013), at school (Lee, 2014), and in play (Schaufeli, 2013). Further, engagement positively relates to well-being metrics such as good health (Song et al., 2022) and more focused attention (Metiu & Rothbard, 2013)

Engagement shapes how individuals interact with their environments or artifacts. Engaged individuals are psychologically present and attentive, connected, integrated, and focused on performance (Rich et al., 2010). In an engaged state, individuals are likely to devote concentrated effort to activities over time without getting distracted (Fredricks et al., 2004; Mollen & Wilson, 2010) and will thus experience a positive and fulfilling state of mind while doing so (Schaufeli et al., 2002).

Being engaged with an AI enables individuals to experience outcomes such as focused attention and arousal while performing tasks (Bui et al., 2015; Deng & Poole, 2010; Hess et al., 2005; Kanfer & Ackerman, 1989; Park et al., 2007). Accordingly, we view AI Engagement as an overarching psychological state of being involved with an AI artifact resulting in performance outcomes. Specifically, we define AI engagement as an active state of mind where the individual's involvement in an AI activity or artifact is characterized by affective, behavioral, and cognitive manifestations. We conceptualize AI engagement as a superordinate, second-order construct composed of three reflective, first-order dimensions: Affective, behavioral, and cognitive engagement.

Affective Engagement refers to the degree of positive emotions that the user of an IS artifact feels while interacting with the artifact—i.e., the sense of enjoyment one feels while interacting with an IS artifact. Thus, we define *affective engagement as the extent to which an individual cares about and experiences enjoyment with a specific AI artifact.* When affective engagement is high, users are happy to interact with the artifact and experience a sense of positive well-being. Users who are highly affectively engaged can discern a difference between their emotional state before and after using the AI artifact.

Behavioral Engagement refers to the observable actions of a user with an AI artifact. This dimension of engagement focuses on behaviors related to AI usage that can be explicitly observed as actions where users exert more effort, exhibit more task persistence, or actively seek help (Pintrich & Schunk, 2002). Since behavioral engagement can be defined in terms of both effort and persistence, we propose a definition of AI behavioral engagement that is applicable to both situations: *behavioral engagement is the extent to which individuals exert observable effort and exhibit persistence in remaining involved with an AI artifact.* When behavioral engagement is high, users remain physically (in person or digitally) and actively connected with the AI artifact.

Cognitive Engagement refers to the complete absorption in an AI artifact (Agarwal & Karahanna, 2000; Csikszentmihalyi & Csikzentmihaly, 1990; May et al., 2004; Webster & Ahuja, 2006). A well-known conceptualization of cognitive engagement is the concept of "flow" (Csikszentmihalyi & Csikzentmihaly, 1990). Flow is "the state in which action follows upon action according to an internal logic which seems to need no conscious intervention"(Csikszentmihalyi, 2014, p.136). Even though there may be considerable intellectual effort associated with the use of the AI artifact, engagement itself is reflected in how absorbed an individual is with the activity even if there is some discomfiture associated with the mental exercise. Accordingly, we define *cognitive engagement as the extent to which an individual becomes intellectually absorbed with an AI artifact.* When cognitive engagement is high, users become oblivious to their surroundings and lose track of the passage of time (Agarwal & Karahanna, 2000).

2.2 Social Cognitive Theory

Social Cognitive Theory (SCT) (Bandura, 1991) provides a robust theoretical lens to explain the relationship between AI Engagement and its antecedents and consequences. SCT is a psychological framework that emphasizes the dynamic interplay between personal factors, environmental influences, and behavior. It posits that individuals learn by observing and imitating others, particularly those they perceive as role models or influential figures in their social environment. The theory highlights the cognitive processes involved in learning, such as attention, retention, reproduction, and motivation. SCT has been widely applied in various fields, including education, psychology, and IS, to explain and predict behavior change and design effective interventions that take into account the social context and cognitive processes involved in learning.

Central to SCT is the notion of self-efficacy, or an individual's belief in their capacity to execute behaviors necessary to produce specific performance attainments. As users gain familiarity with AI tools, they may develop stronger self-efficacy beliefs regarding their ability to effectively utilize these tools, which can lead to greater engagement. This dynamic is also underscored by observational learning, another key element of SCT, where users learn by observing others, increasing their familiarity, and fostering greater engagement with AI tools. Thus, SCT provides a comprehensive framework for understanding how individuals increasingly engage with technology as they learn about the technology and develop familiarity with it through observation, modeling, and self-efficacy.

2.3 AI Familiarity and Engagement

AI technologies are often intelligent agents – applications that perceive their environment, mimic human cognitive functions, to take or suggest actions towards a goal (Gams et al., 2019; Riedl, 2019). AI can be divided into General and Narrow AI. While General AI is a possibility in the future, Narrow AI currently has most impact in the workplace. General AI possesses the ability to understand, learn, and apply knowledge across a wide range of tasks, essentially mimicking human-like cognitive functions. Narrow AI, on the other hand, specializes in performing a specific task or a set of closely related tasks, lacking the broad cognitive capabilities inherent in General AI. Narrow AI can be one of four types (Huang & Rust, 2018): Mechanical intelligence refers to AI performing routine, repeated tasks that do not require much learning or novel responses. Analytical intelligence refers to AI processing information for the purpose of learning and problem solving (Sternberg, 1984). Intuitive intelligence refers to AI holistically integrating previous learning to adapt to novel situations (Sternberg, 2005). Finally, empathetic intelligence refers to AI recognizing and understanding user emotions and responding appropriately to them (Goleman, 2020; Johnson, 2014). AI agents should be designed such that they incorporate varying degrees of each type of intelligence depending on the nature of the assistance required by the user. AI can also be classified as archetypes that vary in their decision-making autonomy from limited to expansive: a) Reflexive (e.g., Apple Siri), b) Supervisory (e.g., recommenders), c) Anticipatory (e.g., media compilation applications), and d) Prescriptive (e.g., conversational agents) (Baird & Maruping, 2021). The focus of this paper is on Narrow AI artifacts.

Building upon the foundational principles of SCT, we argue that the concept of familiarity with AI artifacts is a critical antecedent to engagement. Familiarity with an AI tool acts as a catalyst for engagement as it reduces cognitive load and uncertainty, thereby enhancing the user's comfort and willingness to engage with(Venkatesh et al., 2012) the AI artifact (Novak et al., 2000). This reduction in cognitive load directly facilitates a user's ability to focus on higher-level tasks and interactions with the AI artifact, rather than grappling with the basics of tool operation (Sweller, 1988). Furthermore, familiarity has been shown to foster a sense of competence and mastery, which are key drivers of intrinsic motivation and, by extension, (Deci & Ryan, 1985). Therefore, it stands to reason that familiarity with an AI tool would be positively related to Engagement with the AI artifact.

While research on AI familiarity specifically is scarce, past research provides evidence to suggest a positive relationship between technology familiarity and user engagement. For instance, Li et al. (2014) found a positive association between the familiarity with online gaming platforms and user engagement with them. This relationship was also supported by Fütterer et al. (2023), who found that students demonstrating a significant level of proficiency—a construct similar to familiarity—with digital technologies also exhibited increased engagement with e-learning tools. Thus, we propose:

H1: AI artifact familiarity is positively related to AI Engagement.

2.4 Engagement and Intention to Use

SCT also provides a strong argument to explain the relationship between AI Engagement and intention to use an AI tool. From the SCT lens, engagement is driven by a combination of self-efficacy, observational learning, and outcome expectations. Engaging with an AI tool can reinforce self-efficacy beliefs, supporting an individual's confidence in their ability to use the tool effectively, which, as Bandura (1991) argues, directly influences intentionality. Engagement also cultivates observational learning, thereby enabling users to acquire requisite skills and confidence, further fostering their intention to use the tool.

Furthermore, in the context of AI, outcome expectations could manifest as anticipated efficiency gains, improved decision-making, or even career advancement. When users engage with an AI tool and experience positive outcomes, even on a small scale, it reinforces their outcome expectations, thereby strengthening their intention to continue using the tool (Venkatesh, Thong, & Xu, 2012). This is particularly relevant in organizational settings where the utility of AI tools is often measured in terms of productivity gains or cost savings (Devaraj & Kohli, 2003).

Moreover, the interplay between self-efficacy, observational learning, and outcome expectations can create a virtuous cycle. As users engage with the AI tool, their self-efficacy and observational learning increase, which in turn positively influences their outcome expectations. These heightened outcome expectations then serve to further motivate engagement and solidify the intention to use the AI tool (Bandura, 1991; Compeau & Higgins, 1995).

Existing literature also provides ample evidence that user engagement influences the intention to use different technologies. For instance, cognitive, affective, and behavioral engagement all were shown to have a positive impact on intention to use innovative mobile banking applications (Hepola et al., 2020). Similarly, increased engagement with relevant online platforms was found to significantly predict users' intention to persist in their use (Al Amin et al., 2022). Engagement was also found to be an important determinant in students' continued application of e-learning tools (Tawafak, AlFarsi, et al., 2021). In addition, Hepola et al. (2020) found that psychological engagement has a stronger association with continuance intention than does attitude or satisfaction when service consumption is driven by hedonic reasons. Agarwal and Karahanna (2000) showed that that cognitive engagement positively affected perceived usefulness and ease of use, leading to an increase in intention to use an AI artifact. Accordingly, we hypothesize:

H2: AI Engagement is positively related to intention to use the AI artifact.

Figure 1 shows the full conceptual research model.

3. Method

A sample of 258 undergraduate students from a public university in the South-East United States participated in the study. All subjects were enrolled in the same undergrad course. Their participation was voluntary; they received a small amount of extra course credit if they participated in the experiment. The mean and standard deviation of the age of participants was 21.5 years and 5.18 respectively with 43% male. Further, the sample included 47.7% While, 15.5% Asian/Pacific Islander, 6.2% Black or African American, 22.9% Hispanic or Latino, and 7.8% Others.

After receiving an initial briefing and providing their consent, subjects were directed to a web browser where they had to interact with a generative AI tool, DALL.E2, for at least 10 minutes. During that time, subjects asked DALL.E2 to generate pictures based on

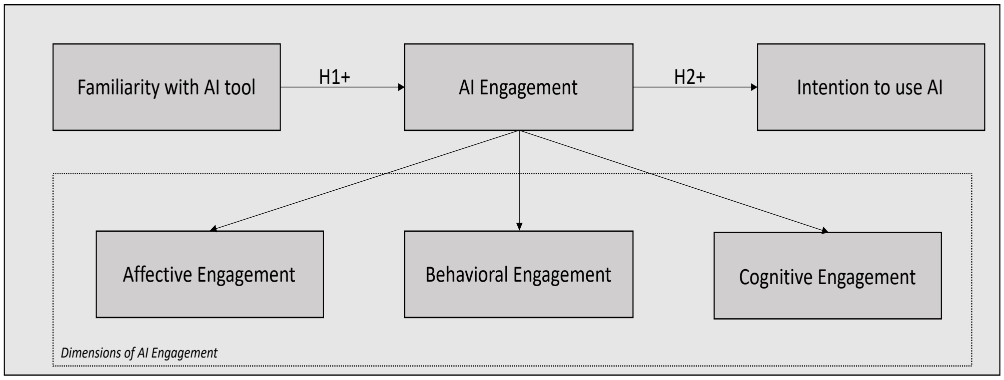


Figure 1. Research model.

the verbal directions they gave to the AI (e.g., an abstract painting of a cat jumping off a building into a cup of soup). They were asked to generate multiple pictures. Upon completion of the task, the subjects completed surveys on their familiarity with the AI tool, AI Engagement, intention to use the AI tool in the future, and demographics (age, gender, and race).

We used the following measures (see Appendix A for full scale details):

- *Intention to use*. Intention to use was assessed using a three item scale adapted from the Behavioral Intention to Use scale by Davis (1989). The three items represented statements and the subjects were asked to indicate the extent to which they felt that the statements were true. Subjects indicated their responses on a 5-point Likert-type scale (1 = Strongly disagree; 5 = Strongly agree).
- *AI Engagement*. AI engagement was measured using a 15 item scale adapted from (*self-citation*), covering three different dimensions, namely affective engagement, behavioral engagement, and cognitive engagement. The dimensions were measured using 5, 6, and 4 items respectively. Each item represented a statement and subjects were asked to indicate their agreement using a 5-point Likert-type scale (1 = Strongly disagree; 5 = Strongly agree).
- *Familiarity with AI tool*. This scale was specifically created for this study. It consisted of two questions: “What is your degree of familiarity with this type of generative AI tool?” and “Have you used DALL.E2 before?”.

4. Results

We tested the hypotheses by examining the relationships between *AI Engagement* and *AI tool familiarity,* as well as *AI Engagement* and *intention to use* the AI tool through structural equation modeling (SEM) using AMOS 27.0. We conducted a CFA ($\chi^2(160) = 332.14$; CFI = 0.95; RMSEA = 0.065) to assess the fit of the items with the five intended first-order constructs (AI tool familiarity, intention to use the AI tool, and the three engagement subscales). We present the correlations among the first order constructs in Table 1 along with the descriptive statistics. Further, we present Cronbach’s alpha, composite reliability, and average variance extracted (AVE) of the first-order constructs in Table 2. The values of composite reliability and AVE are satisfactory for all first-order constructs except for AI familiarity. We computed the second order AI engagement construct by taking the average scores of the three first-order engagement constructs. (The results of a Confirmatory Factor Analysis are included in Appendix B.)

The findings support H1 and H2 as the correlations between AI Engagement and Familiarity with AI tool and intention to use are positive and significant as shown in Table 1. Further, we tested the hypothesis using structural equation modeling (AMOS) and the path model is presented in Figure 2.

The model’s fit statistics were satisfactory with $\chi2(165) = 353.35$; CFI = 0.95; and RMSEA = 0.067. Figure 2 shows the model and the results from the structural model analysis. *AI tool familiarity* has a significant path coefficient to the higher-order AI Engagement construct and that higher-order AI Engagement has a significant path coefficient to *intention to use* the AI tool. The effect of *AI tool familiarity* was positive and significant. Further, the effect of *AI Engagement* on the *intention to use* the AI tool was also positive and significant.

Table 1. Mean, SD, and Correlation.

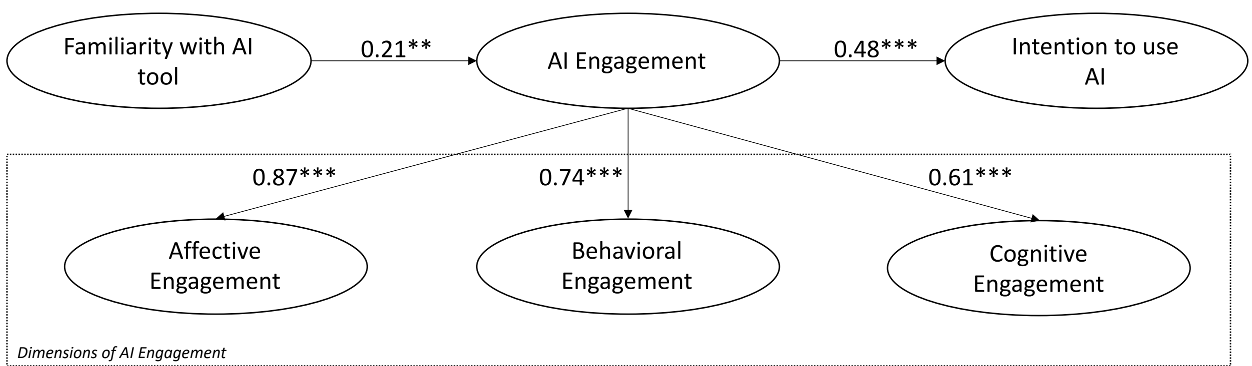
	Mean	***SD***	**AFF**	**BEH**	**COG**	**AI_ENG**	**AI_FAM**	**ITU**
AFF	3.87	0.84	1					
BEH	4.12	0.72	.608**	1				
COG	3.12	1.06	.479**	.404**	1			
AI_ENG	3.70	0.71	.837**	.778**	.821**	1		
AI_FAM	1.51	0.55	.171*	.081	.208**	.198*	1	
ITU	4.84	1.05	.395**	.201**	.336**	.390**	.303**	1

*Notes: **correlation is significant at the 0.01 level (2-tailed); *correlation is significant at the 0.05 level (2-tailed). N = 258. AFF: Affective Engagement; BEH: Behavioral Engagement; COG: Cognitive Engagement; AI_ENG: AI Engagement; AI_FAM: AI tool familiarity; ITU: Intention to Use.*

Table 2. Cronbach's alphas, Composite Reliability, and AVE.

	Cronbach's alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
AFF	0.92	0.93	0.72
BEH	0.90	0.91	0.62
COG	0.90	0.91	0.71
AI_FAM	0.42	0.58	0.43
ITU	0.86	0.87	0.69

Notes: N = 248. AFF: Affective Engagement; BEH: Behavioral Engagement; COG: Cognitive Engagement; AI_FAM: AI tool familiarity; ITU: Intention to Use



Model Fit Indices χ^2=353.35 with d.f. 165, CFI=0.95, RMSEA=0.067
*p<0.1;**p<0.05;***p<0.01

Figure 2. Structural Path Model.

5. Discussion and conclusions

The results show that familiarity with AI tools is significantly associated to engagement with such tools. Furthermore, AI engagement is significantly associated related to the intention to use such tools in the future. In other words, our study highlights the critical role of AI engagement as an antecedent to the intention to use AI.

Our research makes several theoretical contributions. First, it illustrates the how Social Cognitive Theory is a useful theoretical lens through which to study the role of engagement in the context of technology adoption. Second, we contribute to IS theory by conceptualizing AI engagement as a second-order superordinate (reflective) construct which explain and predicts intention to use. This conceptualization of AI engagement is new to the literature.

From a practical perspective, our findings suggest that organizations have to consider deliberate approaches to introduce new AI tools to employees. Employees have to be afforded time to get acquainted with a new AI tool, so that they can strengthen their self-efficacy. Learning about new tools can be facilitated, for example, through observations and peer testimonies. Furthermore, as employees start trying new AI tools out or use them during a pilot period, it will be informative to measure their engagement. Such measurements can provide important insights into the likelihood of the successful adoption of the new AI tools.

A number of limitations have to be considered when interpreting the results of our research. First, our AI familiarity scale unfortunately showed low reliability. In future studies, we intend to revisit this scale in order to strengthen it. Second, our subjects may have had more reason to be engaged (extra credit) than subjects that chose not to participate in our samples. Yet, table 1 shows that there was an adequate range of engagement levels, which indicates that we did not exclusively recruit highly engaged individuals. Finally, the past few years have seen unprecedented technological advances in the area of AI. As more advanced AI tools become even more widespread, levels of familiarity may become uniformly high.

For future research, we intend to replicate our study design to other forms of AI, including different examples of generative AI. We also intend to collect field data from a large organization in the region of the lead author's university that uses AI to support a number of complex decision-making tasks. Finally, we plan to expand our research model with a number of additional constructs that may moderate the hypothesized relationships, such as AI anxiety, social presence, satisfaction with process, and commitment to task outcomes.

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Appendix A. Scales used

AI Engagement (self-citation)
Instructions: The following statements refer to your experience while completing the task. Please rate the degree to which you agree with each statement (1 = Strongly disagree; 5 = Strongly agree).

Affective Engagement:
1. It made me happy to complete this task.
2. It was fun to complete this task.
3. I care about the content of this task.
4. I enjoyed completing this task.
5. It was interesting to complete this task.

Behavioral Engagement:
1. I completed this task as I was expected to.
2. I made an effort to complete this task in its entirety.
3. I carefully followed the instructions for this task.
4. I was being attentive to the task.
5. I was actively involved in completing this task.
6. I diligently completed this task.

Cognitive Engagement:
1. This task was so absorbing that I forgot about everything else.
2. I did not think about anything else when completing this task.
3. I was fully immersed while completing this task.
4. This task took up all of my attention.

Intention to Use (Davis 1989)
Instructions: The following statements refer to your experience while completing the task. Please rate the degree to which you agree with each statement (1 = Strongly disagree; 5 = Strongly agree).

1. I intend to use the DALL.E2 in the next six months.
2. I can predict when I will use the DALL.E2 in the next six months.
3. I plan to use the DALL.E2 in the next six months.

Familiarity with the AI Tool
Instructions: Please answer the following questions:
1. What is your degree of familiarity with this type of generative AI tool?
    a. No Familiarity: This is my first time doing anything like this.
    b. Some Familiarity: I have dabbled with AI tools like this but not much.
    c. Decent Familiarity: I have good experience with this or similar AI tools like ChatGPT.
    d. Extreme Familiarity: I use this tool or similar AI tools on a daily basis.
2. Have you used DALL.E2 before?
    a. Not at all
    b. A few times
    c. Several times

Demographics
- How old are you?
- What is your gender? (Male/female/other/prefer nor to answer)
- Please specify your ethnicity. (White/Black or African American/Hispanic or Latino/Native American/Asian or Pacific Islander/Other)

Appendix B. CFA Standardized Item Loadings

Items	Mean	S.D.	Loadings
AFF_ENG1	3.73	1.02	.879
AFF_ENG2	4.03	0.94	.906
AFF_ENG3	3.53	1.01	.652
AFF_ENG4	3.91	0.95	.906
AFF_ENG5	4.13	0.89	.858
BEH_ENG1	4.02	0.97	.613
BEH_ENG2	4.07	0.93	.745
BEH_ENG3	4.27	0.80	.768
BEH_ENG4	4.14	0.87	.831
BEH_ENG5	4.18	0.82	.887
BEH_ENG6	4.05	0.89	.855
COG_ENG1	3.04	1.24	.851
COG_ENG2	3.04	1.21	.897
COG_ENG3	3.35	1.19	.914
COG_ENG4	3.04	1.16	.694
AI_FAM1	1.88	0.89	.833
AI_FAM2	1.14	0.41	.414
ITU1	6.04	1.19	.895
ITU2	5.51	1.21	.643
ITU2	2.98	1.19	.924

Notes: AFF: Affective; BEH: Behavioral; COG: Cognitive; AI_FAM: AI Familiarity; ITU: Intention to Use; ENG: Engagement; N=258