To Be Credible or to Be Creative? Understanding the Antecedents of User Satisfaction with AI-Generated Content from a Cognitive Fit Perspective

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Abstract

Generative artificial intelligence (GAI) has the potential to fundamentally disrupt how content is produced and will become increasingly integrated into organizational and individual task-performing and decision-making. This study aims to investigate how individuals perceive and process AI-generated content. Specifically, we propose that perceived credibility and creativity are critical antecedents of user satisfaction via cognitive fit and examine the boundary conditions. In an online scenario experiment with a sample size of 548 participants, we tested our hypotheses. The result shows that perceived credibility and creativity positively impact cognitive fit, which in turn affects user satisfaction with the outcome and process. Furthermore, regarding the boundary conditions, the results indicate a good match between the information values (i.e., credibility and creativity) and task types (i.e., routine vs. creative task) leads to cognitive fit, and users perceive different levels of satisfaction when they have different task motivations (i.e., hedonic vs. utilitarian task). Finally, we discuss theoretical contributions and practical implications.

Keywords: AI-generated content, ChatGPT, cognitive fit, creativity, credibility

1. Introduction

Generative artificial intelligence (GAI) refers to artificial intelligence (AI) algorithms that generate original outputs from given prompts. GAI is capable of processing trained data to generate content similar to that created by humans, and has the potential to fundamentally disrupt how content is produced (Dwivedi et al., 2023). GAI will become increasingly integrated into organizational and individual task-performing and decision-making (van Dis et al., 2023). Traditionally, certain human activities (e.g., writing, composing, and painting), particularly those involving highly ***creative*** processes, have been assumed to be impossible to automate by non-human entities. However, GAI tools (e.g., ChatGPT) have suddenly transformed this fundamental assumption as GAI has become available for multiple tasks such as music composing (Sun et al., 2023), news writing (Jang et al., 2022), and image creation (Campbell et al., 2022) in much less time and expense. ChatGPT (Chat Generative Pre-trained Transformer) is a generative language model released by OpenAI in late 2022 that enables users to converse with machines on a broad range of topics. OpenAI now nears 1 billion monthly users as the fastest-growing website in the world, according to new data (Digital Information World, 2023). Since its launch, GAI has generated widespread conversation across various fields, including IS, as the impact of its ability to create new forms of content on research and practice will be transformative and disruptive (Dwivedi et al., 2023; Lund et al., 2023).

Like the AI technology that once fundamentally transformed IS research, GAI tools will also impact the assumptions underlying information systems (IS) domains (Dwivedi et al., 2023). In order to have a better understanding of the impact of GAI on research and practice, scholars have proposed the opportunities, challenges, and implications in various domains of research (Dwivedi et al., 2023; Gursoy et al., 2023; Lund et al., 2023; Paul et al., 2023; van Dis et al., 2023). These studies all suggested that GAI tools have both positive and adverse impacts. On the one hand, GAI, as a decision support system (DSS), presents the human aspects of task processing, such as ***creativity*** and conceptual thought. Creativity refers to the extent to which AI-generated content is original, unexpected, appropriate, and relevant (Casaló et al., 2021). For instance, the GAI tool can become an innovator of a human-AI collaboration team (Dwivedi et al., 2023). On the other hand, the dark sides of GAI include fake text, misinformation, and biased information (Dwivedi et al., 2023; Paul et al., 2023). These significant drawbacks result in information ***credibility*** concerns, which can lead to severe consequences, for example in GAI-based decision systems, where unreliable GAI responses can lead to the decision failure. Moreover, creativity and credibility are two key constructs of information values (Setyani et al., 2019). Based on prior studies on

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information values, this study represents AI-generated information values through the constructs of perceived credibility and perceived creativity.

Existing literature on GAI has focused on challenges, opportunities, and research directions (Dwivedi et al., 2023). Despite the growing popularity of GAI, empirical studies investigating how users process this AI-generated information are still limited. In line with Dwivedi et al. (2023), our core proposition is that GAI will fundamentally challenge the assumptions in the IS fields as AI technology once did. Therefore, this study reviews research on AI technology in the IS field and draws on relevant theory to develop a research framework. According to emerging research, such GAI tools like ChatGPT are critical to the success of digital platforms in the foreseeable future (Dwivedi et al., 2023; Gursoy et al., 2023; Lund et al., 2023; Paul et al., 2023; van Dis et al., 2023). Considering their great potential to offer a major boost to ***creativity*** in various contexts while also presenting challenges for organizations and individuals regarding the ***credibility*** of information, it is of great theoretical and practical importance to understand *how users perceive and process AI-generated content from the perspective of the information values.* Moreover, explaining user satisfaction via information technology has long been an important IS research area (Cheng et al., 2020). Prior research suggests that it is important to keep users satisfied with AI because user satisfaction is closely associated with their continuous usage. Therefore, this study tries better to understand the antecedents of user satisfaction with GAI, and we propose our first research question: *RQ1. How do perceived credibility and creativity impact user satisfaction?*

Research shows that when task information is presented in a format that matches a user's cognitive style, it results in cognitive fit (Giboney et al., 2015). Prior studies employ the term "cognitive fit" to describe the degree to which a task's environmental factors match the nature of the task (Giboney et al., 2015). This study defines cognitive fit as the user's subjective evaluation of the appropriateness of AI-generated content. Considering that satisfaction attainment theory proposes perceived goal attainment (i.e., cognitive fit) as the antecedent of satisfaction and cognitive fit theory offers a theoretical framework to understand how information presentation impacts user satisfaction via cognitive fit (Vessey, 1991), we propose to model user satisfaction from the perspective of cognitive fit to answer the first question. This theory has been used to explain the mechanism of the effect of information presentation in AI contexts, such as chatbots (Chen et al., 2021), knowledge-based systems (Giboney et al., 2015), and augmented reality (Shiau & Huang, 2023). Moreover, predictors of the values of information generated by GAI can be categorized as either cognitive (e.g., ***credibility***) or affective (e.g., ***creativity***) (Setyani et al., 2019). The two-dimensional information values serve as perceptual antecedents that affect users' cognitive evaluations of information (Setyani et al., 2019).

Furthermore, some studies have posited that users' psychological perception is inconsistent across all task scenarios (e.g., John & Kundisch, 2015; Wu & Lu, 2013). However, the lack of empirical research on GAI has poorly delineated the boundary conditions of cognitive fit and satisfaction. That is, existing research has yet to delineate for which specific task types, and under which task motivations, users are more inclined to perceive cognitive fit and satisfaction with the content generated by GAI. Given the algorithm resources invested in GAI, generating content indiscriminately regardless of task types might cause unnecessary waste. Therefore, it is urgent to identify the boundary conditions in this context, and we propose our second research question: *RQ2. What are the boundary conditions that impact cognitive fit and user satisfaction?*

Cognitive fit theory also posits that a good match between the information presentation and ***task types*** leads to a higher problem-solving outcome (Chen, 2017). Moreover, according to the motivation theory, users' psychological response is different for different ***task motivations*** (Wu & Lu, 2013). John & Kundisch (2015) called for a more comprehensive perspective that would extend existing literature to explain the mechanism and boundary conditions of cognitive fit. However, the potential moderating effect of task type and motivation in the context of GAI remains poorly understood. Therefore, this study tries to provide a nuanced understanding of the AI-generated content by detecting boundary conditions of task types and motivations.

We conducted an online scenario experiment (n = 548) to answer the two research questions. We designed four scenarios corresponding to two factors: task types (routine/creative) and task motivation (hedonic/utilitarian) (2*2). Our findings provide valuable theoretical contributions and practical implications by advancing theoretical understanding of the antecedents of user satisfaction with GAI from the perspective of cognitive fit and investigating boundary conditions in different AI-generated task scenarios.

2. Theoretical foundation

2.1. Generative AI

Generative artificial intelligence (GAI) refers to AI algorithms that generate original outputs from given prompts (Dwivedi et al., 2023). GAI has successfully imitated some aspects of the critical characteristics of human creativity. Moreover, GAI has become available for multiple tasks, such as news, literature, music, and painting creation. Since most of the GAI tools available for individual users have just been released, the existing literature on GAI has focused on challenges, opportunities, and research directions (Dwivedi et al., 2023). The few individual-level studies in GAI contexts have focused on users' perceptions of AI-generated content. For example, Jang et al. (2022) also examined how prior knowledge moderates the users' evaluations of AI-generated news. Campbell et al. (2022) constructed a general framework to understand better how users respond to AI-generated images. However, these studies do not deconstruct the mechanisms by which users perceive and process AI-generated content to form satisfaction. Considering that cognitive fit theory is suitable for understanding this mechanism, this study tries to reveal the central role of cognitive fit in fostering user satisfaction.

2.2. Cognitive fit theory

Cognitive fit theory establishes a theoretical framework for understanding how information presentation impacts user satisfaction via cognitive fit (Vessey, 1991). According to the theory, a good match between the information and task presentation leads to a higher problem-solving outcome (Chen, 2017). Specifically, information presentation refers to the way the information is presented as an aid to solving that task, and task presentation refers to the task that the user is expected to complete (J. V. Chen et al., 2021). In the context of AI-generated content, we conceptualize information presentation as the credibility and creativity of the AI-generated content, which are the significant information values that help the user perform tasks.

Cognitive fit theory has been used to explain the mechanism of the effect of information presentation on user's task performance in various contexts, such as chatbot (Chen et al., 2021), knowledge-based systems (Giboney et al., 2015), and online and offline shopping (Garaus et al., 2015; Hong et al., 2004). According to cognitive fit theory, the correspondence between information and task representation allows users to develop a more accurate mental representation (i.e., cognitive fit) of the task (Speier, 2006). Cognitive fit occurs when information representation accentuates the same types of task representation, resulting in more effective task performance (Giboney et al., 2015). Therefore, in this study, we operationalize users' subjective performance evaluation as their satisfaction with outcome and process, which are the two components of satisfaction in the satisfaction attainment theory (Ivanov & Cyr, 2014).

2.3. Satisfaction attainment theory

Satisfaction refers to an affective arousal with a positive valence that an individual feels towards some object (Briggs et al., 2006). In the IS field, satisfaction is one of the most widely examined constructs for assessing the success of IT artifacts (Cheng et al., 2020). Prior studies have divided satisfaction into two distinct dimensions: satisfaction with outcome and satisfaction with process (Cheng et al., 2020; Reinig, 2003). It is important to differentiate between satisfaction with outcome and satisfaction with process, as users may be satisfied with the task-performing outcome but dissatisfied with the process (Ivanov & Cyr, 2014). Specifically, satisfaction with outcome refers to the users' overall affective arousal concerning what was created and accomplished in the task, while satisfaction with process refers to the affective arousal with the tools and procedures used in the task (Ivanov & Cyr, 2014).

The IS literature provides several perspectives on satisfaction theories in different contexts, such as attainment perspectives, confirmation perspectives, and attribute perspectives (Briggs et al., 2008). For instance, satisfaction attainment theory proposes perceived goal attainment as the antecedent of satisfaction and examines the satisfaction with outcome on satisfaction with propose (Briggs et al., 2006). Perceived goal attainment refers to the evaluation of the perceived benefits expected to achieve the goals (Ivanov & Cyr, 2014). In this study, we operationalize cognitive fit as goal attainment because the degree of goal attainment and the perceived cognitive fit are closely related when users use GAI to perform tasks (Dwivedi et al., 2023). Furthermore, cognitive fit leads to satisfaction. Prior research has examined the effect of cognitive fit on user satisfaction in different technological contexts, such as e-learning (Lin, 2012), knowledge systems (Sun et al., 2016), and augmented reality (Shiau & Huang, 2023).

2.4. Task types and task motivations

From the user's point of view, there are two main types of tasks. The creative or routine type of task is defined by four characteristics of the task: structure or not, convergent or divergent thinking, additive or cyclic processing, and information recall or combination (routine task or creative task) (John & Kundisch, 2015). Prior studies on cognitive fit theory have examined individuals form a mental representation (i.e., cognitive fit) of the task based on their own experiences in a variety of routine tasks, such as the searching and browsing tasks in e-commerce platform (Chen, 2017;

Chen et al., 2021; Hong et al., 2004) and shop environment tasks (Garaus et al., 2015). This cognitive fit is derived through the integration of the information and task type. These cognitive fit theory studies have addressed only one type of task: routine tasks. However, in today's business landscape, creative tasks hold significant importance because creativity is a key driver of individual and organizational competitiveness (John & Kundisch, 2015). Moreover, GAI is gaining interest and momentum among scholars and practitioners because the large language model possesses many parameters that enable GAI to leverage deep learning techniques for generating creative content (Dwivedi et al., 2023). Therefore, extending the boundary of cognitive fit theory from a single routine task scenario to a holistic perspective has important theoretical and practical implications (John & Kundisch, 2015).

Task motivation refers to anticipated benefits a task will provide (Garaus et al., 2015). IS research has widely recognized that individuals utilize IS tools for hedonic and utilitarian motivations (Tafesse, 2021). Specifically, users perform tasks with GAI for two reasons: to gain enjoyment (hedonic task) and to acquire information (utilitarian task). Hedonic-oriented users strive to fulfill the task effectively. The task motivation for these users is extrinsic, emphasizing task performance and productivity (Tafesse, 2021). In contrast, utilitarian-oriented users' motivation is intrinsic, emphasizing enjoyment and emotional experience (Garaus et al., 2015). This dual motivation has been examined in various contexts of IS tools, such as the use of mobile apps (Tafesse, 2021), virtual advisor (Li & Mao, 2015), and AI assistants (Yuan et al., 2022). However, the potential moderating effect of this dual motivation on user satisfaction in the context of GAI remains poorly understood (Paul et al., 2023). With this gap in mind, the study investigates the boundary conditions in the relationship between cognitive fit and user satisfaction.

3. Research model and hypotheses

For the purposes of this study, drawing on cognitive fit theory and satisfaction attainment theory, we examined how perceived credibility and creativity affect cognitive fit, which in turn impacts satisfaction with outcome and process. We further used multiple group analysis across different task types (routine/creative task) and task motivations (hedonic/utilitarian task). Figure 1 summarizes the research model of this study. The hypotheses and the corresponding constructs will be discussed in the following sections.

Credibility refers to the degree to which the source and its information are perceived as believable (Xiao & Benbasat, 2007). According to cognitive response theory, when information is perceived as more credible, cognitive responses toward the information are more favorable (Setyani et al., 2019). GAI is expected to generate reliable and trustworthy information (Paul et al., 2023), and in that case, credibility can effectively reduce uncertainty and increase willingness in receiving information. Moreover, prior research has recognized the significance of information credibility in determining users' acceptance of the information from DSS, such as recommendation agents (Xiao & Benbasat, 2007) and AI chatbots (Li & Mao, 2015). We thus hypothesize that the credibility of GAI will influence users' cognitive evaluations of the GAI.

H1a. Perceived credibility is positively associated with cognitive fit.

As a task-performing IS tool, the effectiveness of GAI depends on whether users follow its output. Prior studies indicate that creativity is recognized a key antecedent of information effectiveness because creative content can grab more attention and lead to positive attitudes about the content (Lee & Hong, 2016; Setyani et al., 2019). Creative AI-generated content is seen by users as more original, which can satisfy the users' need for novelty and lead to positive reactions in users (e.g., cognitive appraisal). Motivation, GAI is expected to generate original, revolutionary, and unconventional content (Dwivedi et al., 2023). Therefore, creative AI-generated content meets the users' expectations of GAI, and we propose that:

H1b. Perceived creativity is positively associated with cognitive fit.

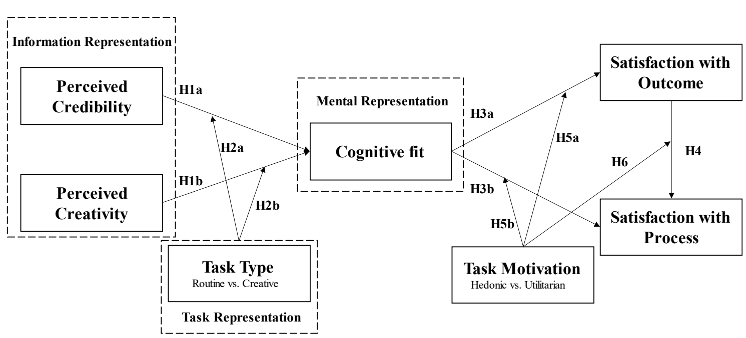

Figure 1. Research model

Cognitive fit theory posits that the performance of a DSS is the result of the interplay of information representations and task types (Giboney et al., 2015). According to the theory, users' problem-solving efficiency increases when task-information complexity is reduced due to their limited capacity to process information (Giboney et al., 2015). Since the way information is received affects how it is processed, information representation can enhance cognitive fit and reduce the cognitive effort when they support the strategies required to perform the task (C.-W. Chen, 2017). Collectively, according to cognitive fit theory and task characteristics, when a correspondence between credibility and routine task or creativity and creative task occurs, users are more likely to perceive AI-generated content as meeting their expectations. We thus propose that:

H2a&H2b. The relationship between perceived credibility (creativity) and cognitive fit is stronger when performing routine (creative) tasks than when performing creative (routine) tasks.

According to the satisfaction attainment theory, satisfaction is an emotional response associated with the achievement of goals (Briggs et al., 2006). Cognitive fit is a desired goal achievement state, meaning that the user perceives that the IS tools respond to the task needs appropriately (Giboney et al., 2015). This comprehension aligns with our research proposition that the cognitive process after interacting with GAI will impact user satisfaction. Moreover, cognitive fit results in a positive perception of IS tools and tasks. Cognitive fit facilitates improved performance outcome evaluation and reduced cognitive effort during task-performing, leading to increased perceived satisfaction with outcome and process (Cheng et al., 2020). Therefore, we propose that users develop experience-based cognitive perceptions after interacting with the GAI, and when this cognition is aligned with the post-use experience, user satisfaction will subsequently increase:

H3a&H3b. Cognitive fit is positively associated with satisfaction with outcome (process).

Satisfaction attainment theory further posits that there is an associated link between satisfaction with outcome and process (Briggs et al., 2006; Mejias, 2007). The satisfaction attained in accomplishing a specific result is a goal in itself, as individuals often seek specific goals that are satisfying to them in terms of their deliverables (Mejias, 2007). Therefore, when such a specific goal is achieved, the user will likely feel satisfied with the process used to achieve that outcome (Reinig, 2003). Furthermore, in the GAI context of this study, users evaluated the outcome of task performance with less cognitive effort than the process of interacting with the GAI, so satisfaction with outcome can be used as a cue to evaluate the human-GAI interaction process. We propose that:

H4. Satisfaction with outcome is positively associated with satisfaction with process.

Considering the different effects of hedonic and utilitarian motivations on the dimensions of satisfaction, in line with prior studies on dual task motivation (Garaus et al., 2015; Tafesse, 2021), we consider task motivation as a moderating variable. A meta-analysis concluded that utilitarian motivation has stronger impacts than hedonic motivation when the user values the perceptions of the deliverables of the tasks (i.e., outcome) while hedonic motivation has stronger impacts than utilitarian motivation when the user values overall perception regarding the procedures of using IS tools (i.e., process) (Wu & Lu, 2013). Therefore, from a holistic perspective of the relationship between cognitive fit and satisfaction, we propose that:

H5a&H5b. The relationship between cognitive fit and satisfaction with outcome (process) is stronger when the task motivation is utilitarian (hedonic) than when the task motivation is hedonic (utilitarian).

Furthermore, regarding the moderator effect of task motivation on the relationship between satisfaction with outcome and process, prior research posited that tasks with different motivations lead to differences in users' goal achievement, resulting in significant differences in satisfaction with outcome and process (Mejias, 2007). Considering that users with utilitarian motivations value goal achievement and holistic task performance more than users with hedonic motivations (Wu & Lu, 2013). We thus propose that:

H6. The relationship between satisfaction with outcome and satisfaction with process is stronger when the task motivation is utilitarian than when the task motivation is hedonic.

4. Research methodology

4.1. Experimental design

We tested our hypotheses by conducting an online scenario experiment. This approach enabled us to assess the respondents' mental representation by exposing them to scenarios that resembled actual human-GPT interaction contexts (Vance et al., 2015). Following the task and interaction scenario exposition, respondents were requested to answer questions related to the scenarios. The scenario-based experiment served to enhance the authenticity of the assessments made by participants and their declared viewpoints. We designed four scenarios corresponding to two factors: task types (routine/creative) and task motivation (hedonic/utilitarian) (2*2). Each of the four scenarios contained a unique combination of task type and task motivation to measure the effects of task type and task motivation.

To manipulate the routine task and creative task, in line with the prior research (John & Kundisch, 2015), we considered searching for high-score movies and laptop performance indicators as routine tasks and creating short stories and writing academic reports as creative tasks. As for the treatment of task motivation, in line with the definitions of utilitarian and hedonic tasks (Wu et al., 2020), creating short stories and searching for high-score movies were typical hedonic tasks, and writing academic reports and searching for laptop performance indicators were typical utilitarian tasks.

We chose ChatGPT as the context for our experiment due to its popularity, with nearly 1 billion monthly users, making it the fastest-growing GAI website in the world (Digital Information World, 2023). ChatGPT has garnered significant attention and has the potential to radically transform a wide variety of tasks related to language (Lund et al., 2023). In real-life and work settings, ChatGPT is a great choice for users who want to use GAI to complete the four tasks in the scenarios, as ChatGPT has demonstrated its capability in performing these four tasks (Dwivedi et al., 2023).

4.2. Procedure

The procedure of the online scenario experiment is depicted in Figure 2. First, we explained the information about the experiment to the respondents. Second, the respondents were randomly assigned to one of four task scenarios. Third, the respondents were asked to answer some questions about the assigned task. Fourth, each respondent was presented with a scenario (corresponding to the task in Step 2) that mimicked the user's interface with ChatGPT (version 3.5). Specifically, we asked the participants to imagine that they were interacting with ChatGPT to complete a given task. Participants were then shown a screenshot of an actual interaction scenario we had previously conducted using ChatGPT. This screenshot represented a genuine interaction between a user and ChatGPT and was carefully selected to closely align with the given task. Finally, after exposure to the task and interaction scenarios, the respondents were asked to report their demographics and answer questions regarding the other constructs.

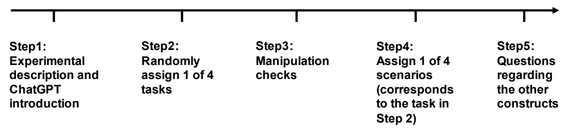

Figure 2. Scenario experiment procedure

4.2. Manipulation checks and measures

To check our manipulation of the routine/creative and utilitarian/hedonic treatment, we asked respondents to rate two sets of statements (1 = strongly disagree, 7 = strongly agree). The manipulation checks of the task type relied on the three items adapted from John & Kundisch (2015) (e.g., the task requires divergent thinking). The manipulation checks of the task motivation relied on the three items from Benoit & Miller (2019) (e.g., the task is to experience pleasure, not to achieve a goal). A t-test analysis indicated significant differences in the mean score of "task type" between routine task ($M = 3.42$) and creative task ($M = 6.03$, $p < 0.001$), as well as between "task motivation" scores for the hedonic task ($M = 5.05$) and utilitarian task ($M = 2.43$, $p < 0.001$). Therefore, the t-test results confirmed the validity of our manipulations.

All constructs within the research model were measured utilizing scales established in prior studies, with minor adjustments made to fit the research context. Specifically, perceived credibility (e.g., the content generated by ChatGPT is trustworthy) was measured with items adapted from Li & Mao (2015). Perceived creativity (e.g., the content generated by ChatGPT is unconventional) was measured with items adapted from Casaló et al. (2021). Cognitive fit (e.g., the content generated by ChatGPT is a good representation of such a task) was measured with items adapted from Garaus et al. (2015). Satisfaction with outcome (e.g., I am satisfied with content generated by ChatGPT in completing this task) and satisfaction with process (e.g., I feel satisfied with the way ChatGPT generates content) were measured with items adapted from Ivanov & Cyr (2014). All items were rated on a seven-point Likert scale from 1 (strongly disagree) to 7 (strongly agree).

4.3 Sample and data collection

Before data collection, we conducted a pretest with 10 IS researchers and 60 respondents to check for the comprehensiveness of the questionnaire and to verify that the effect of the manipulation was as expected. For the main experimental data collection, we recruited 548 respondents online. Each participant received approximately 10 Chinese yuan as compensation for their participation. The online scenario experiment was conducted in April 2023 with the assistance of an MTurk-like platform (wjx.cn) in China and lasted for approximately one week. Our sample comprised 242 males (44.2%) and 306 females (55.8%). Among these 548 respondents, 135 were assigned to the routine-hedonic treatment group (group 1, searching for high-score movies), 138 were assigned to the routine-utilitarian treatment group (group 2, searching for laptop performance indicators), 131 were assigned to the creative-hedonic treatment group (group 3, creating short stories), and 144 were assigned-utilitarian treatment group (groups 4, writing academic reports).

5. Data analysis and results

5.1. Measurement and structural model

This study used SmartPLS 4 for data analysis to test and validate the proposed research model and hypotheses. All the constructs in this study were reflectively measured. The measurement model for all constructs was assessed by examining their reliabilities, convergent validities, and discriminant validities. As presented in Table 1, the composite reliability (CR) values for all the constructs exceeded 0.8, and the average variance extracted (AVE) exceeded 0.5, exceeding the recommended threshold values of 0.7 and 0.5, respectively, confirming appropriate reliability for all constructs. The assessment results indicated that the loadings of all items on their respective constructs were above 0.7, and these loadings surpassed cross-loadings. Hence, these constructs demonstrated adequate convergent and discriminant validities. The correlation of each construct with the others was lower than the square root of its own AVE, and each construct differed from the other constructs, indicating satisfactory discriminant validity for these constructs.

The PLS results showed that both perceived credibility and perceived creativity had significant positive impacts on cognitive fit ($\beta = 0.524$, $t = 14.537$, $p < 0.001$; $\beta = 0.208$, $t = 5.314$, $p < 0.001$, respectively; two-tailed test, the same below), lending support to H1a and H1b. Cognitive fit was found to have significant impacts on satisfaction with outcome and satisfaction with process ($\beta = 0.592$, $t = 16.701$, $p < 0.001$; $\beta = 0.289$, $t = 6.310$, $p < 0.001$, respectively), lending support to H3a and H3b. Satisfaction with outcome significantly positively impacted satisfaction with process ($\beta = 0.552$, $t = 12.052$, $p < 0.001$), lending support to H4. Perceived credibility and perceived creativity explained collectively 38.6% of the variance in cognitive fit. Cognitive fit explained 35.0% of the variance in satisfaction with outcome. Cognitive fit and satisfaction with outcome explained 57.7% of the variance in satisfaction with process.

5.3. Multiple-group analysis (MGA)

Given the categorical nature of the task type and task motivation ranging from (1) routine task to (2) creative task and (1) hedonic task to (2) utilitarian task, respectively, we conducted an MGA analysis to test the hypothesis related to task type and task motivation differences. Specifically, we used SmartPLS 4 for MGA across different task types and task motivations. The MGA results showed that the relationship between perceived credibility and cognitive fit was stronger when performing routine tasks than when performing creative tasks ($\Delta\beta = 0.250$, $p < 0.01$), while the relationship between perceived creativity and cognitive fit was stronger when performing creative tasks than when performing routine tasks ($\Delta\beta = -0.296$, $p < 0.001$). Therefore, H2a and H2b were supported. Moreover, the relationship between cognitive fit and satisfaction with outcome is stronger when the task motivation is utilitarian than when the task motivation is hedonic ($\Delta\beta = -0.165$, $p < 0.05$), while the relationship between cognitive fit and satisfaction with process is stronger when the task motivation is hedonic than when the task motivation is utilitarian ($\Delta\beta = 0.211$, $p < 0.05$). The relationship between satisfaction with outcome and satisfaction with process is stronger when the task motivation is utilitarian than when the task motivation is hedonic ($\Delta\beta = -0.226$, $p < 0.01$). Therefore, H5a, H5b, and H5c were supported. Table 2 presents these MGA results.

Table 1. Descriptive statistics, reliabilities, and correlations

Construct	Mean	SD	AVE	CR	(1)	(2)	(3)	(4)	(5)
(1) Cognitive Fit	5.695	0.924	0.594	0.814	**0.771**				
(2) Perceived Credibility	5.614	1.044	0.552	0.831	0.589	**0.743**			
(3) Perceived Creativity	5.000	1.378	0.733	0.892	0.371	0.31	**0.856**		
(4) Satisfaction with Outcome	5.856	0.939	0.577	0.845	0.592	0.57	0.327	**0.76**	
(5) Satisfaction with Process	5.906	0.894	0.520	0.812	0.616	0.588	0.333	0.723	**0.721**
Note: Boldfaced diagonal elements are the square roots of AVE									

6. Discussion

6.1. Key findings

With the development of GAI in various fields, it is important to understand what and how AI-generated content values can enhance user satisfaction. This study explores the underlying psychological mechanism and boundary conditions of users' reactions to GAI.

First, regarding the underlying mechanism, this study shows that two aspects of AI-generated content information values (i.e., credibility and creativity) have significant influence on cognitive fit, which in turn positively impacts user satisfaction.

Second, regarding boundary conditions, the MGA results show that users may respond differently when performing different tasks and having different motivations. Specifically, the relationship between perceived creativity (credibility) and cognitive fit is stronger when performing creative (routine) tasks than when performing routine (creativity) tasks. Moreover, the relationship between cognitive fit and satisfaction with process (outcome) is stronger when the task motivation is hedonic (utilitarian) than when the task motivation is utilitarian (hedonic), and the relationship between satisfaction with outcome and satisfaction with process is stronger when the task motivation is utilitarian than when the task motivation is hedonic.

6.2. Implications for research

The theoretical implications of this study are two-fold. First, this study empirically investigates the antecedents of user satisfaction with GAI tools. Most of the prior research on GAI has been conceptual in nature (e.g., Dwivedi et al., 2023; Lund et al., 2023). The rapid advancements in GAI have opened up new opportunities for research in IS. Due to the disruptive characteristics of GAI and its transformative implications, more research is urgently needed in this emerging context (van Dis et al., 2023). By drawing on cognitive fit theory (Garaus et al., 2015) and recent work on information values (Kim et al., 2022; Setyani et al., 2019), we advance the current understanding of GAI user satisfaction by viewing satisfaction formation as a cognitive evaluation process. In doing so, this study identifies perceived credibility and creativity as key predictors of user satisfaction and theorizes the central role of cognitive fit in formulating user satisfaction. Moreover, this study distinguishes user satisfaction with outcome and process and extends the applicability of cognitive fit theory and satisfaction attainment theory to the context of GAI for the first time.

Second, this study investigates the boundary conditions that impact cognitive fit and user satisfaction by finding task type and motivation to be notable moderators. Specifically, this study examines the task type and motivation differences at both the cognitive fit and satisfaction attainment stage. John & Kundisch (2015) called for a more comprehensive perspective to explain the mechanisms and boundary conditions of cognitive fit, as previous cognitive fit research has addressed only one of the two main task types (i.e., routine tasks and creative tasks) that exist: routine tasks. Our study answers this call, and we examined the moderator effect of both two task types on the relationship between information values and cognitive fit. Moreover, studying users' hedonic and utilitarian motivation to use GAI can provide insights to explain their satisfaction with AI-generated content further.

The revealed relationships among information values, cognitive fit, satisfaction and boundary conditions not only extend prior research on cognitive fit theory and satisfaction attainment theory, but also provide evidence for explaining how users perceive and process AI-generated content.

Table 2. Multiple-group analysis results

Hypothesis	**Routine task** (n=273)	**Creative task** (n=275)	**Δβ**	**MGA** p-value	**Hypothesis support**
H2a: PCD→CF	0.618 (0.043)	0.368 (0.060)	0.250	0.001	Support (**Routine＞Creative**)
H2b: PCT→CF	0.084 (0.050)	0.380 (0.053)	-0.296	＜0.001	Support (**Creative＞Routine**)
Hypothesis	**Hedonic task** (n=266)	**Utilitarian task** (n=282)	**Δβ**	**MGA** p-value	**Hypothesis support**
H5a: CF→SO	0.503 (0.058)	0.668 (0.041)	-0.165	0.018	Support (**Utilitarian＞Hedonic**)
H5b: CF→SP	0.381 (0.058)	0.169 (0.056)	0.211	0.013	Support (**Hedonic＞Utilitarian**)
H5c: SO→SP	0.451 (0.052)	0.677 (0.055)	-0.226	0.006	Support (**Utilitarian＞Hedonic**)
Note: PCD = perceived credibility, PCD = perceived creativity, CF = cognitive fit, SO= satisfaction with outcome, SP = satisfaction with process. The numbers in parentheses represent standard deviations.					

6.3. Implications for practice

The findings aid GAI-based digital platforms and GAI developers. First, practitioners should take two types of AI-generated content values as two critical indicators of cognitive fit and recognize their roles in promoting user satisfaction. Second, our results indicate that a good match between the information value and task type leads to cognitive fit. Besides considering creativity and credibility, practitioners should also focus on the match between information credibility (creativity) and routine (creative) task. Specifically, developers can allow the GAI to identify whether the task type is more routine or creative and thus adjust the GAI parameters automatically. For example, Temperature is a parameter that controls the diversity of the generated results in GPT-4, the higher the parameter, the more diverse the generated results. Third, practitioners can consider identifying users' task motivations for using GAI and develop corresponding content-generation strategies.

6.4. Limitations and future research

Although our findings are valuable, some methodological and practical limitations need to be considered. First, we exclusively chose one GAI tool (i.e., ChatGPT) to serve as the research scenario. We propose that our research model and findings are inclined to exhibit external validity because ChatGPT is a representative GAI tool and now nears 1 billion monthly users as the fastest-growing GAI tool in the world. Thus, we encourage subsequent research to investigate this issue by filtering the GAI tools (e.g., music, painting, and video generation tools). Further analysis and future research are necessary to establish generalizability across different platforms and GAI tools. Second, the scenario experiment allows us to assess respondents' mental representation by providing respondents with scenarios resembling real human-GPT interaction situations. However, future research could set up task scenarios for respondents in advance and collect data after they actually interact with the GAI tool to enhance the validity of our conclusions.

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