I Can't Take This Anymore! Understanding the Relationship Between Personality Traits and Tolerance of Generative AI Hallucinations

***Abstract*—The use of generative AI has increased drastically in recent years, offering transformative potential in creativity, productivity, and decision-making across various domains. However, concerns are growing among practitioners and academics about its tendency to produce inaccurate or nonsensical outputs—a phenomenon known as generative AI hallucinations. While scholars have begun exploring this phenomenon, most of the existing research focuses on technical issues and solutions. This research takes a behavioral approach to examine the association between individual personality traits and tolerance of generative AI hallucinations. Drawing on Error Management Theory and the Big Five personality traits, we examine how individuals with different personality traits tolerate generative AI hallucinations. The study contributes to calls from management journals to investigate the challenges associated with generative AI use. Our findings provide important theoretical implications and offer actionable insights for engineering managers seeking to implement generative AI.**

***Managerial Relevance Statement*—This research provides actionable guidance for engineering managers for using generative AI effectively. Managers can leverage employees' personality traits to assign more tolerant individuals (e.g., those high in agreeableness and openness) to creative or exploratory tasks involving generative AI. Managers can also implement features that help users with lower tolerance for generative AI hallucinations (e.g., those high in conscientiousness or extraversion) verify AI outputs. Additionally, managers can design targeted, personality-informed training programs to help employees critically evaluate generative AI outputs and mitigate the impact of hallucinations. Finally, managers can use the findings from this research to develop teams with diversity in personality traits to potentially reduce over-reliance on generative AI outputs.**

***Index Terms*—Artificial intelligence (AI), generative artificial intelligence (GAI), generative artificial intelligence hallucinations (GAIH), personality traits, tolerance of generative artificial intelligence hallucinations (TGAIH).**

I. INTRODUCTION

Recent advancements in computing hardware and algorithms have led to the development of generative AI, which can create human-like content [1], [2]. Taking notice, individuals have started using generative AI for tasks such as information search, content creation, and data analysis [1], [2]. Generative AI use is increasing across industries and domains [3]. For example, generative AI is now used to write code and identify errors in software development [4]. Similarly, generative AI is used to develop novel campaign images and slogans in marketing [5]. In summary, generative AI is here to stay, and many individuals within and outside organizations rely on its content-generating capabilities to improve productivity [6], [7], [8].

The rise of generative AI has also been accompanied by significant media and scholarly attention [2]. Within just two months of its launch, OpenAI's generative AI, ChatGPT reached over 100 million users, a record-breaking achievement for a technology [9], [10], [11]. Industry reports by McKinsey & Company and Boston Consulting Group further highlight the sharp increase in individual-level generative AI use over the past year [7], [12]. However, the increasing use of generative AI has revealed the issue of generative AI hallucinations, a phenomenon in which generative AI provides misleading information [13], [14]. For example, generative AI falsely accused a law professor of sexual harassment [15]. Similarly, generative AI provided fictitious citations that led to sanctions against two New York lawyers [16].

In this paper, we explore the relationship between individual personality traits and tolerance of generative AI hallucinations. Our motivation to examine the tolerance of generative AI hallucinations is based on the increasing use of generative AI among individuals [7], [17]. This increasing use of generative AI is likely to increase instances of receiving generative AI hallucinations. Therefore, individuals may reach a tolerance threshold where they find hallucinations unacceptable and choose to discontinue using the technology [18]. The tolerance for generative AI hallucinations can differ widely across individuals, possibly as a result of underlying personality-driven differences [19]. Therefore, we focus on personality traits because these traits can be different across individuals, represent the core characteristics of an individual and are generally consistent and persistent across the individual's lifetime [20], [21]. More importantly, personality traits are predictive of an individual's attitudes, actions, and behaviors [22].

Research is needed to understand the relationship between personality traits and tolerance of generative AI hallucinations. Scholars have argued that individuals enthusiastically and optimistically receive newer technologies [23]. More importantly, this positive outlook on novel technologies has often led practitioners and researchers to overlook the challenges associated with technology use in the long run [24], [25]. Recognizing the need for a balanced view of technologies, scholars have called for research examining the challenges associated with generative AI [26], [27]. Therefore, several scholars have started to examine the emerging phenomenon of generative AI hallucinations [14], [28]. However, this nascent stream of literature suffers from two limitations. First, most of the current literature is primarily focused on the technical aspects of generative AI hallucinations (e.g., classification of different types of generative AI hallucinations) [29], [30]. Second, the few studies that do examine how individuals respond to generative AI hallucinations assume that all individuals respond similarly to generative AI hallucinations [31], [32]. Combining these motivating factors, we examine the following research question:

RQ: How are personality traits associated with tolerance of generative AI hallucinations?

We conducted a survey with 331 participants in the United States on Amazon Mechanical Turk (MTurk) to examine the relationship between personality traits and tolerance of generative AI hallucinations. Our paper makes two key contributions to engineering management literature. First, our paper contributes to the emerging engineering management research on AI, by bringing together previously disparate streams of literature, Error Management Theory, from organizational psychology, and the Big Five personality traits, from personality psychology, to develop a novel theoretical framework for understanding user responses to AI hallucinations, by accounting for individual differences [1], [2], [33], [34], [35]. Second, the paper also contributes to the literature on personality traits by empirically examining their role in shaping user interactions with generative AI [36], [37], [19]. The findings reveal that conscientiousness and extraversion are negatively associated with tolerance for generative AI hallucinations, while openness and agreeableness show positive associations. These insights deepen the theoretical understanding of how personality traits are associated with generative AI hallucinations. Finally, this research also provides important implications for practice.

II. Literature Review

A. Generative Artificial Intelligence (GAI)

Artificial Intelligence (AI) can be broadly defined as “the ability of a machine to perform cognitive functions that we associate with human minds, such as perceiving, reasoning, learning, interacting with the environment, problem-solving, decision-making, and even demonstrating creativity” [38]. Most scholars would agree that the birth of AI took place at the 1956 summer workshop at Dartmouth College [39], [40]. Since then, AI has evolved significantly. With advancements in computing, storage, and algorithms, AI can now generate human-like content in the form of text, images, audio, and even videos [41], [42]. This newer form of AI is generally referred to as generative AI (GAI) [1], [3].

Generative AI represents a transformative leap in technology to generate diverse outputs [2], [43]. In organizational contexts, its integration has shown a potential to augment knowledge-intensive tasks such as research, strategic planning, and creative ideation [44], [45]. Several studies report that generative AI can not only generate content in different modalities but can also improve user productivity in tasks related to software development [46], art creation [47] and customer service [6]. Recognizing the potential opportunities for improving productivity, several organizations have invested in generative AI technologies [7]. Following suit, several academic institutions are developing programs to upskill individuals to leverage generative AI capabilities [48], [49]. However, the use of generative AI can introduce novel challenges that need examination, particularly within engineering management practices.

Examining the challenges associated with generative AI is important for both research and practice. Our review of the recent studies indicates that most of the literature focuses on the positive impacts of generative AI on productivity and creativity [6], [8], [47]. Although such a focus is beneficial for practice and research, it neglects the challenges that come along with the use of generative AI [50]. Prior work on novel technologies, such as social media, provides a cautionary tale [51], [52]. Practitioners and scholars initially tend to focus more on the positive aspects and ignore the challenges that come along with the use of a new technology [24], [25]. Understanding the need to have a balanced view, several academic journals have called for research to examine the challenges associated with generative AI [26], [27]. In this research, we direct our attention to the issue of generative AI hallucinations that has grabbed significant attention in recent years [16], [43], [19]. More importantly, we focus on generative AI hallucinations because this issue does not seem to be solvable in the near future [53].

B. Generative Artificial Intelligence Hallucinations (GAIH)

Generative AI hallucination is an emerging phenomenon that has received significant attention from both academics and practitioners [14], [54]. According to IBM [54] “AI hallucination is a phenomenon wherein a large language model (LLM)—often a generative AI chatbot or computer vision tool—perceives patterns or objects that are nonexistent or imperceptible to human observers, creating outputs that are nonsensical or altogether inaccurate.” Generative AI hallucination can also be defined as “the generated content that is nonsensical or unfaithful to the provided source content” [14]. The launch of Meta’s generative AI called Galactica highlighted the issues of generative AI hallucinations [55]. Galactica was trained on 48 million scientific documents (e.g., papers, textbooks, lecture notes, and wiki-based websites) and was designed to help scientists summarize papers, write code, and solve math problems [56]. However, soon after its launch, Galactica’s users reported fictional citations and inaccurate calculations in the outputs [57]. Although several instances of generative AI hallucinations have been reported since Galactica was shut down, the use of generative AI has only increased among individuals [7].

Recognizing the increasing use of generative AI by individuals, scholars have started to explore and examine generative AI hallucinations [14], [28]. The major stream of literature is technical in nature and explores causes, types, and mechanisms associated with generative AI hallucinations [29], [30]. For example, scholars have developed classifications that describe generative AI hallucinations as intrinsic and extrinsic hallucinations [14]. Intrinsic hallucinations refer to the discrepancy between the generative AI's output and the source data used for training [14], [29]. In contrast, extrinsic hallucinations refer to the generative AI's output that cannot be verified against the source data used for training [14], [29]. Similarly, scholars highlight several technical causes for generative AI hallucinations [14], [58]. For example, generative AI hallucinations can be caused by training data [29]. Since large amounts of data are needed to train generative AI models, they are generally trained on publicly available data on the internet which may be rife with misinformation and biases, may be limited to a specific timeframe, and may lack specialized domain knowledge [29]. As a consequence, generative AI may hallucinate and provide information that is not factually true or has a bias [58].

There is an urgent need to examine the consequences of generative AI hallucinations from a behavioral perspective. Although progress has been made in examining the technical aspects of generative AI hallucinations [28], [29]. Research on individual-level responses to generative AI hallucinations is needed because individuals tend to over-rely on information provided by AI [59], [60]. This over-reliance can be harmful because individuals tend to rely on heuristic thinking and do not critically evaluate the information provided by generative AI [61]. Consequently, individuals are likely to make sub-optimal decisions [59], [62]. To overcome the issue of over-reliance, researchers have started to develop solutions that inform individuals about AI hallucinations [31], [32]. For example, Leiser, et al. [32] developed Hallucination Identifier for Large Language Model (HILL) to highlight hallucinations in generative AI responses and caution users. Although these solutions provide some information to the users regarding generative AI hallucinations, they assume that there are no differences in how individuals respond to generative AI hallucinations. Moreover, the outcome of employing these solutions has not been examined systematically. That is, research is needed to explore how individuals tolerate generative AI hallucinations, defined as the extent to which hallucinations are acceptable to the individual in the use of generative AI [19].

C. Personality Traits

Personality plays a very important role in determining an individual's cognition, emotion, and behavior [22]. Research on personality has evolved over time and personality scholars have successfully transitioned from several disparate personality traits to a few very well-abstracted traits [63]. The "Big Five" model, also known as the five-factor model of personality, is the most established and commonly used scale to measure personality traits in personality research [63], [64]. The model comprehensively represents personality through the set of five traits of agreeableness, conscientiousness, extraversion, neuroticism, and openness [64], [65]. Among the five personality traits listed above, the first trait of agreeableness informs how considerate, kind, cooperative, and compassionate an individual is [66]. The second trait of conscientiousness indicates how self-disciplined, organized, and persistent an individual is [67]. The third trait of extraversion captures and explains how sociable and outgoing an individual is [68], [69]. The fourth trait of openness characterizes how open an individual is to new experiences [70]. Finally, the fifth trait of neuroticism indicates how emotional an individual is [71].

The tolerance of generative AI hallucination can vary widely among users, potentially due to personality-driven differences [19]. For example, agreeable individuals may be more forgiving of hallucinations due to their cooperative and accommodating nature [66], [72]. In contrast, conscientious individuals, who value accuracy, are likely to have lower tolerance for generative AI hallucinations because it conflicts with their goal-oriented and structured approach [73], [74]. Openness may encourage individuals to accept generative AI hallucinations as creative or innovative outputs [75], while neuroticism may amplify negative reactions due to heightened sensitivity to uncertainty and reduce tolerance to generative AI hallucinations [76], [77]. Given the increasing use of generative AI in various domains, examining the interplay between personality traits and tolerance of generative AI hallucinations is essential to designing systems that cater to diverse user needs and preferences.

III. THEORETICAL DEVELOPMENT AND HYPOTHESES

A. Error Management Theory

We develop a theoretical framework using Error Management Theory (EMT) and Big Five personality traits to understand how personality traits are associated with tolerance for generative AI hallucinations (see Figure 1). EMT posits that humans have evolved cognitive mechanisms to minimize the adverse outcomes associated with two types of errors: Type I (false positives) and Type II (false negatives) [78], [79]. EMT also posits that under uncertainty, individuals tend to bias their decision-making toward avoiding the error they perceive as having the most adverse consequences [80]. For example, in evolutionary psychology, men tend to overestimate romantic interest from women (Type I error), while women tend to underestimate male commitment (Type II error) [78]. This bias is theorized to have evolved because the outcome of missing a mating opportunity (for men) or misjudging a partner's long-term intentions (for women) had asymmetric consequences in evolutionary contexts [78], [79].

In the case of generative AI, there is inherent uncertainty regarding hallucinations, as individuals cannot reliably predict whether an output will be factually accurate or misleading. To minimize Type I errors (accepting inaccurate outputs as correct), individuals may adopt a low tolerance for AI hallucinations, scrutinizing responses more critically. Conversely, to minimize Type II errors (rejecting accurate outputs as incorrect), individuals may adopt a higher tolerance, accepting some inaccuracies to retain potentially useful information. We argue that an individual's tolerance for AI hallucinations is shaped by how they perceive these errors through the lens of personality traits. For example, an individual high in conscientiousness may have a lower tolerance for AI hallucinations because of their emphasis on accuracy [73], whereas an individual high in openness may have a higher tolerance for AI hallucinations due to their preference for exploration [70]. By integrating EMT with the Big Five personality traits, this research posits that personality traits have an association with the user's tolerance of generative AI hallucination. This theoretical framework is particularly relevant as generative AI systems become increasingly embedded in decision-making contexts [1].

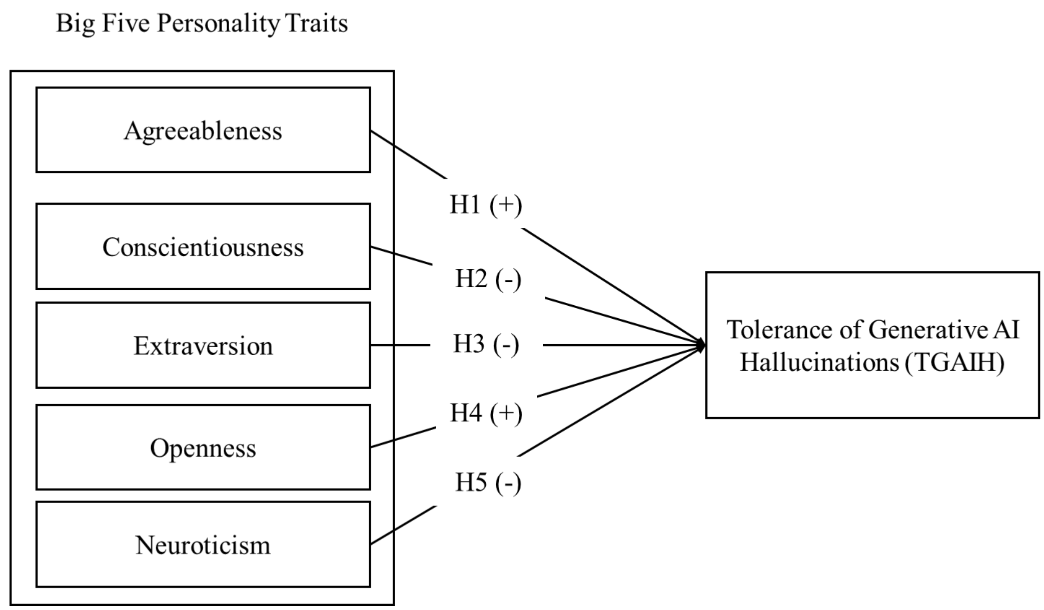

Figure 1. Research Model

B. Agreeableness and Tolerance of Generative AI Hallucinations

The personality trait of agreeableness is generally associated with cooperativeness, kindness, and helpfulness [66]. Agreeable individuals tend to exhibit prosocial behaviors, are considerate, and are forgiving in their interactions [72], [81]. These traits often translate into positive attitudes toward the use of technology [36], [37]. In the context of generative AI, individuals with high agreeableness may be more forgiving of hallucinations, perceiving them as minor imperfections rather than critical flaws [66], [82]. Their cooperative nature makes them more likely to focus on the overall utility of the system rather than fixating on occasional inaccuracies [22], [83]. Additionally, agreeable individuals may prioritize the benefits of generative AI in facilitating collective creativity or problem-solving over its limitations [84]. For instance, an agreeable user might view generative AI hallucinations as opportunities to engage in constructive dialogue or to refine outputs, thereby reframing errors as learning moments [85], [86], [87]. Their focus on fostering harmonious interactions may lead them to downplay the significance of errors, increasing their tolerance [85], [88]. Therefore, individuals high on trait agreeableness are more likely to tolerate generative AI hallucinations.

H1: Agreeableness is positively associated with tolerance of generative AI hallucinations.

C. Conscientiousness and Tolerance of Generative AI Hallucinations

Conscientious individuals exhibit high levels of self-discipline and intrinsic motivation, driving them to take action and consistently strive for improved task performance [67], [73]. Their intense focus on goal attainment and adherence to structured, methodical approaches makes accuracy and precision central to their work [73], [89]. Generative AI hallucinations are likely to conflict with these values and can disrupt the structured approach and goal-directed efforts of conscientious individuals [74], [90]. Moreover, conscientious individuals may invest effort into identifying and correcting hallucinations, but this additional workload could lead to frustration [89], [91], [92]. Their focus on efficiency and precision may make them more inclined to seek alternative tools or solutions that better align with their standards for performance and reliability [91], [92]. Considering the above arguments, we propose the following hypothesis.

H2: Conscientiousness is negatively associated with tolerance of generative AI hallucinations.

D. Extraversion and Tolerance of Generative AI Hallucinations

Extroverts are characterized by their sociable, outgoing, and energetic nature, with a strong emphasis on building and maintaining social connections and interactions [64], [69], [93]. Their motivation to preserve social standing and relationships is likely to lead them to scrutinize outputs from generative AI [92], [93]. For instance, sharing incorrect outputs from generative AI could jeopardize reputation, especially in professional or collaborative settings where reliability is critical. This sensitivity to the social consequences is likely to make extroverts less tolerant of generative AI hallucinations. Furthermore, extroverts' focus on social interactions can create a higher expectation for technology to facilitate effective communication [94], [95], [96]. They are likely to view any inaccuracies in generative AI outputs as a hindrance to achieving their social goals [93], [96]. Therefore, extroverted individuals are less likely to tolerate generative AI hallucinations.

H3: Extraversion is negatively associated with tolerance of generative AI hallucinations.

E. Openness and Tolerance of Generative AI Hallucinations

Individuals high in openness are characterized as curious, willing to explore new ideas, and have a preference for novelty [70], [97]. These individuals are also more likely to have a favorable view of newer technologies [86], [97]. In the context of generative AI, individuals with high openness may perceive hallucinations as part of the system's creative process and an opportunity to explore unconventional outputs [75]. This perspective aligns with their openness to experimentation and their tendency to prioritize innovation [75], [98]. As a result, these individuals are more likely to tolerate generative AI hallucinations. Moreover, openness may lead individuals to engage in adaptive behaviors when encountering generative AI hallucinations. For example, individuals with higher levels of trait openness may actively seek ways to refine and repurpose hallucinated outputs, viewing them as starting points for creative ideation rather than flaws [99]. This flexibility suggests that these individuals may not only tolerate hallucinations but also see value in leveraging them for innovative problem-solving. Therefore, individuals with higher levels of trait openness are likely to have a higher tolerance for generative AI hallucinations. Based on these arguments, we propose the following hypothesis.

H4: Openness is positively associated with tolerance of generative AI hallucinations.

F. Neuroticism and Tolerance of Generative AI Hallucinations

Neuroticism is generally associated with emotional instability, anxiety, fear, irritability and anger [77]. Individuals high in neuroticism often exhibit an exaggerated response to ambiguous or threatening situations, perceiving uncertainty as particularly distressing [100], [101]. This trait is associated with a tendency to overgeneralize negative experiences, making small setbacks feel disproportionately significant [102]. Neurotic individuals are more likely to experience frequent mood fluctuations and feelings of vulnerability [76]. Their strong emotional reactions to perceived risks can amplify their focus on potential errors, compounding their stress and discomfort in unpredictable environments [89]. In the context of generative AI, neurotic individuals are likely to exhibit low tolerance for hallucinations due to their heightened emotional responses to perceived threats and errors [76], [77]. Similarly, generative AI hallucinations are likely to exacerbate the discomfort and stress associated with neuroticism [102]. Therefore, individuals who are high on trait neuroticism are less likely to tolerate generative AI hallucinations.

H5: Neuroticism is negatively associated with tolerance of generative AI hallucinations.

IV. Method

A. Participants

We collected data for this research through a survey by recruiting participants in the United States on Amazon Mechanical Turk (MTurk). We compensated the participants with $1.50 for completing the survey. We used MTurk because it is a reliable platform for data collection and has been widely used for studies across disciplines [103], [104]. We collected 331 responses (229 males and 102 females). The majority of participants had a 4-year college degree and were predominantly in the age range of 31 and 40 years. Additionally, participants had varying levels of income and experience (Please see Appendix A for more details).

B. Measures

We measured the independent variables of Big Five personality traits using a seven-point Likert scale, which ranged from "Strongly Disagree" to "Strongly Agree", that was developed by Goldberg [65]. Although we used the same measures as Goldberg [65] we cannot share these measures in this study due to copyright restrictions. All constructs used in the study were reflective. We chose to use reflective constructs because they align with our theoretical framework, where the indicators (e.g., survey items or measurements) are considered manifestations of the underlying concept. We measured our dependent variable of tolerance of generative AI hallucinations using a scale developed in a pilot study (please see Appendix B for more details on the pilot study for the scale development). We conceptualize tolerance of generative AI hallucinations in line with prior IS use literature, which positions IS use as a broad construct that captures the elements of the user and the system [105], [106]. Age, gender, and education were included as control variables. Additionally, we incorporated several attention-check questions to ensure data quality and participant attentiveness.

V. Analysis and Results

A. Statistical Analysis

We employed Partial Least Squares Structural Equation Modeling (PLS-SEM), specifically utilizing Smart PLS 4 software, to examine the hypotheses. Initially, we tested the convergent and discriminant validities of the measurement model. Our analysis revealed that Cronbach's alpha and reliability values exceed the threshold of 0.7, indicating strong composite reliabilities [107]. Furthermore, all Average Variance Extracted (AVE) values surpass the 0.50 threshold, signifying convergent validity for all constructs in the study (Please see Appendix B for more details).

Next, we assessed discriminant validity through various approaches. Initially, we applied the Fornell and Larcker [108] criterion test, comparing the square root of the Average Variance Extracted (AVE) of each construct with the correlation between pairs of constructs. Our findings indicated that all square root of AVE values exceeded their correlations with other constructs, suggesting satisfactory discriminant validity [108]. These outcomes are provided in Table I. Additionally, we examined item cross-loadings and observed high loading values on their respective constructs and lesser values on other constructs, as depicted in Table II. To ensure that the measures of the tolerance of generative AI hallucinations measure one construct, we ran a factor analysis and found that the measures load on only one factor.

We also utilized the Heterotrait-Monotrait Ratio (HTMT) matrix, as introduced by Henseler, et al. [109] to further assess discriminant validity. Our analysis revealed that all HTMT matrix values remained below the recommended threshold (0.90) established by Hair Jr, et al. [107] and Henseler, et al. [109]. Also, all VIFs are less than the threshold of 3.0.

TABLE I
CORRELATIONS FORNELL-LARCKER CRITERION

	TGAIH	**Ag**	**Co**	**Ex**	**Open**	**Ne**
TGAIH	**0.818**					
Ag	0.602	**0.800**				
Co	-0.640	-0.432	**0.862**			
Ex	-0.571	-0.460	0.518	**0.842**		
Open	0.565	0.673	-0.521	-0.512	**0.790**	
Ne	0.436	0.334	-0.601	-0.538	0.471	**0.878**

Note: *The diagonal bold values are the square roots of AVE.*

TABLE II
CROSS-LOADINGS

	TGAIH	**Ag**	**CO**	**Ex**	**Open**	**Ne**
TGAIH _1	**0.767**	0.442	-0.468	-0.459	0.461	0.377
TGAIH _2	**0.822**	0.484	-0.538	-0.509	0.438	0.414
TGAIH _3	**0.846**	0.564	-0.553	-0.439	0.455	0.33
TGAIH _4	**0.814**	0.439	-0.501	-0.492	0.444	0.374
TGAIH _5	**0.825**	0.451	-0.504	-0.437	0.482	0.340
TGAIH _6	**0.837**	0.530	-0.573	-0.493	0.478	0.351
TGAIH _7	**0.789**	0.527	-0.499	-0.446	0.449	0.318
TGAIH _8	**0.845**	0.494	-0.544	-0.467	0.491	0.358
Ag_1	0.509	**0.781**	-0.371	-0.373	0.491	0.294
Ag_2	0.501	**0.832**	-0.321	-0.310	0.549	0.183
Ag_3	0.461	**0.805**	-0.345	-0.353	0.526	0.243
Ag_4	0.451	**0.781**	-0.345	-0.445	0.592	0.356
Co_1	-0.554	-0.311	**0.880**	0.613	-0.476	-0.537
Co_2	-0.569	-0.424	**0.818**	0.611	-0.437	-0.466
Co_3	-0.562	-0.381	**0.867**	0.602	-0.415	-0.511
Co_4	-0.517	-0.372	**0.884**	0.650	-0.468	-0.561
Ex_1	-0.491	-0.385	0.582	**0.849**	-0.442	-0.617
Ex_2	-0.476	-0.369	0.591	**0.829**	-0.423	-0.614
Ex_3	-0.524	-0.428	0.641	**0.851**	-0.413	-0.612
Ex_4	-0.422	-0.363	0.601	**0.837**	-0.453	-0.648
Open _1	0.491	0.580	-0.413	-0.373	**0.828**	0.325
Open _2	0.443	0.467	-0.515	-0.405	**0.796**	0.422
Open _3	0.399	0.547	-0.298	-0.448	**0.743**	0.379
Ne_1	0.398	0.287	-0.487	-0.576	0.403	**0.862**
Ne_2	0.353	0.322	-0.521	-0.681	0.388	**0.873**
Ne_3	0.358	0.263	-0.536	-0.636	0.390	**0.896**
Ne_4	0.406	0.271	-0.553	-0.672	0.399	**0.892**

Ne_5	0.395	0.325	-0.541	-0.678	0.485	**0.869**

B. Results

We utilized SmartPLS along with a bootstrapping procedure to evaluate the hypotheses [107]. We created an index to measure tolerance of generative AI hallucinations by taking the average of the eight items for tolerance of generative AI hallucinations. The personality traits constructs accounted for 56% of the variance in tolerance of generative AI hallucinations. Our findings indicate that four of the five personality traits are significantly associated with tolerance of generative AI hallucinations. We found that agreeableness (β = 0.309; p < 0.001; f-square = 0.110) and openness (β = 0.116; p < 0.1; f-square = 0.014) exhibit a positive association with tolerance of generative AI hallucinations. Conscientiousness (β = -0.365; p < 0.001; f-square = 0.131) and extraversion (β = -0.146; p < 0.1; f-square = 0.014) demonstrate a negative association with tolerance of generative AI hallucinations. Unfortunately, our hypothesis regarding the association with neuroticism (H5) was not supported by the data. We also found that out of all the control variables, only education had a significant and positive association with tolerance of generative AI hallucinations. The results are summarized in Table III.

TABLE III
RESULTS

	Coefficient	**t statistics**	**p-values**
Ag -> TGAIH	0.309	3.857	0.000
Co -> TGAIH	-0.365	4.117	0.000
Ex -> TGAIH	-0.146	1.369	0.086
Open -> TGAIH	0.116	1.520	0.064
Ne -> TGAIH	-0.035	0.443	0.329
Age -> TGAIH	0.042	0.875	0.191
Education -> TGAIH	0.096	2.397	0.008
Gender ->TGAIH	0.023	0.281	0.389
R-square	0.560		

C. Robustness Checks

We conducted a series of analyses to assess the robustness of our results. Initially, we investigated the potential for nonlinearity in the structural model by examining quadratic effects. Our findings suggest that not all quadratic effects are significant. Subsequently, we employed the Gaussian copula approach to explore potential endogeneity. Tests were conducted for every possible combination of Gaussian copulas. The results indicate that none of the Gaussian copulas are significant, implying that the structural model remains unaffected by endogeneity, thus reinforcing its robustness [110]. Finally, we employed the FIMIX-PLS approach to evaluate unobserved heterogeneity in PLS path models. The optimal number of segments is computed based on the minimum size required for each segment. To ensure an effect size of 0.15 and a power level of 80%, a minimum sample size of 85 per segment is advised [110]. Based on this guideline, we utilized four segments and conducted four separate tests ranging from one to four segments [110]. The outcomes, depicted in Table IV, yielded inconclusive results. For example, AIC and AIC3 suggest a four-segment solution, while AIC4 and CAIC indicate a three-segment solution. MDL5 proposes differing segment solutions. Consequently, these analyses collectively fail to definitively identify a particular segmentation [110]. Thus, the presence of unobserved heterogeneity in the model is not deemed critical. Overall, our model's robustness is affirmed through the conducted robustness checks.

TABLE IV
FIT INDICES FOR THE ONE-TO-FOUR-SEGMENT SOLUTIONS

Test	**Number of Segments**			
	1	2	3	4
AIC	682.676	494.268	429.096	**393.488**
AIC3	690.676	511.268	455.096	**428.488**
AIC4	698.676	528.268	**463.488**	481.096
BIC	713.093	558.904	527.951	**526.562**
CAIC	721.093	575.904	**553.951**	561.562
MDL5	**898.761**	953.449	1131.372	1338.859
EN	0	0.622	**0.455**	0.482

D. Common Method Bias

Concerns about common method bias (CMB) often arise when the same questionnaire and response method are used to collect data for both dependent and independent variables [111]. To reduce social desirability bias, we assured participants that their responses would remain anonymous, following best practices in research ethics [111]. After data collection, we conducted several independent tests to assess the potential impact of common method bias. We performed Harman's single factor test (SFT) which showed that a single factor accounted for 32.16% of the variance, which is less than the 50% threshold, indicating no issue with CMB [111]. According to the guidelines, a VIF higher than 3.3 might indicate significant collinearity and the presence of CMB

[112]. The VIFs in our study ranged from 1.39 to 2.65, all of which are below 3.3, indicating no evidence of CMB [112]. We also checked to see if any pair of constructs had a correlation coefficient greater than 0.90 [113]. This is important because methodological bias can artificially inflate observed correlations due to spurious covariance [114]. Upon reviewing the data in Table I, we found that no correlations exceeded the threshold. Therefore, our tests suggest that CMB did not impact our findings.

VI. Discussion

Generative AI has gained widespread popularity in recent years, significantly influencing how individuals within and outside organizations approach decision-making tasks [7]. However, as generative AI systems are increasingly used, the issue of hallucinations has emerged as a critical challenge [43]. Recognizing the importance of generative AI use, many scholars have started to examine generative AI hallucinations [14], [28]. While technical research has explored the causes and potential solutions to these errors, the current stream of research overlooks behavioral aspects of user interaction with generative AI that are equally important [14], [26], [27]. Drawing on Error Management Theory (EMT) and Big Five personality traits, we develop a theoretical framework to examine how personality traits are associated with tolerance of generative AI hallucinations. We propose and empirically examine five hypotheses.

We examine our hypotheses by conducting a survey and find that the results are generally aligned with the proposed hypotheses. First, Hypothesis 1 predicts that agreeableness is positively associated with tolerance of generative AI hallucinations. Our results indicate that agreeableness has a positive and significant association with tolerance of generative AI hallucinations ($\beta = 0.309$; $p < 0.001$). Therefore, we find support for Hypothesis 1. This finding highlights that individuals with higher levels of trait agreeableness are indeed tolerant of generative AI hallucinations. This finding also complements prior literature which indicates that individuals with higher levels of agreeableness are more considerate and forgiving and have positive attitudes toward technology use [72], [81], [37]. Second, Hypothesis 2 indicates that conscientiousness is negatively associated with tolerance of generative AI hallucinations. We find that conscientiousness has a negative and significant association with tolerance of generative AI hallucinations ($\beta = -0.365$; $p < 0.001$). Therefore, we find support for Hypothesis 2 and our conjecture that individuals high on trait conscientiousness are less likely to tolerate generative AI hallucinations. This finding complements evidence from prior literature that individuals with higher levels of conscientiousness tend to avoid hindrances and are more focused on achieving their goals [74], [90], [115]. Third, Hypothesis 3 states that extraversion is negatively associated with tolerance of generative AI hallucinations. Our analysis indicates that extraversion has a negative and marginally significant association with tolerance of generative AI hallucinations ($\beta = -0.146$; $p < 0.1$). Therefore, we find support for Hypothesis 3. The finding is in line with our theorization that individuals with higher levels of extraversion are less likely to tolerate generative AI hallucinations because they are concerned about their social status [69], [96]. Fourth, Hypothesis 4 proposes that openness is positively associated with tolerance of generative AI hallucinations. The results show that openness has a marginally significant positive association with tolerance of generative AI hallucinations ($\beta = 0.116$; $p < 0.1$). Therefore, we find support for Hypothesis 4. The results support our reasoning that individuals with higher levels of openness are more willing to learn and more open to newer technologies [70], [86], [97]. Consequently, these individuals are more likely to tolerate generative AI hallucinations. Finally, Hypothesis 5 indicates that neuroticism is negatively associated with tolerance of generative AI hallucinations. Unfortunately, our results indicate that although the effect is in the proposed direction, it is not significant ($\beta = -0.035$; $p = 0.329$). Therefore, we do not find support for Hypothesis 5. Prior literature indicates that individuals with higher levels of neuroticism tend to avoid focusing on the functional aspects of AI [116]. We think that our hypothesis on neuroticism was not supported because our use cases focused on the functional use of generative AI.

A. Theoretical Contributions

The paper makes two important contributions to the literature. First, our research enriches the emerging engineering management literature on AI, particularly on the phenomenon of generative AI hallucinations—outputs that are factually inaccurate [1], [2], [33], [34], [35]. The paper also extends Error Management Theory into the domain of generative AI by exploring the association between personality traits and tolerance of generative AI hallucinations. We develop a framework by integrating EMT with the Big Five personality traits, proposing that tolerance for hallucinations is shaped by an individual's predispositions to minimize negative outcomes from specific error types [78], [80]. Individuals high in conscientiousness, extraversion, and neuroticism are theorized to exhibit lower tolerance for hallucinations due to heightened aversion to Type I errors (accepting inaccurate outputs). In contrast, individuals high in agreeableness and openness are theorized to exhibit higher tolerance for hallucinations to minimize Type II errors (rejecting potentially useful outputs). The results from our empirical analysis are generally aligned with this theorization, as four of the five theorized relationships are supported. Applying EMT to generative AI, we emphasize the role of individual-level error perception.

Second, the paper contributes to the management literature on personality traits by empirically investigating their role in shaping user interactions with generative AI. Drawing on the Big Five personality traits, we extend their applicability to the context of generative AI hallucinations, a context that has not been previously explored [36], [37], [19]. The findings demonstrate that personality traits such as conscientiousness and extraversion are negatively associated with tolerance for generative AI hallucinations. In contrast, openness and agreeableness are positively associated with tolerance for generative AI hallucinations. By connecting personality traits to user behavior in generative AI contexts, this research deepens our theoretical understanding of the interplay between individual differences and challenges associated with the continued use of generative AI systems. The findings from this research contribute to existing management literature that examined the relationship between personality traits in other contexts of social media, technology use, and virtual teams [117], [118], [119], [120]. For instance, prior research on social media indicates that agreeableness and openness are positively associated with augmented reality immersive experiences on social media [120]. In contrast, agreeableness and openness do not have an impact on team decision quality in the context of virtual teams [119]. These findings highlight similarities and differences in how personality traits impact outcomes across domains of social media, virtual teams, and generative AI.

B. Practical Implications

The paper provides valuable practical implications on how engineering managers can navigate the complexities of generative AI use while considering its current limitations. We have provided four practical implications below that utilize individual personality traits data. Engineering managers should ensure that any use of personality traits data to assign individuals to AI-related tasks or to customize generative AI interactions follows strict legal and ethical guidelines. This includes adhering to regulations such as the General Data Protection Regulation (GDPR) and the California Consumer Privacy Act (CCPA) [121], [122]. Engineering managers should obtain explicit informed consent from employees, ensure non-discrimination, and conduct thorough ethical evaluations before deployment of customized solutions that use personality traits data.

First, rather than assuming that generative AI must be universally used, this research encourages individuals in organizations to critically evaluate the contexts in which generative AI can deliver concrete value. Several organizations conduct personality tests on their employees to effectively utilize employee skills [123], [124]. Engineering managers can use the results of these tests and personality insights from this research to align generative AI use with tasks where its strengths, such as creativity or ideation, outweigh the risks associated with hallucinations. For example, individuals with higher levels of agreeableness and openness, who are more tolerant of generative AI hallucinations, can be strategically assigned to tasks that rely on generative AI outputs for brainstorming or exploratory projects.

Second, instead of adopting a deterministic approach that assumes all organizations must deploy generative AI to remain competitive, this research highlights the importance of a balanced and ethical approach to implementation. Engineering managers could use generative AI cautiously by incorporating features that allow users to verify outputs, thus mitigating the risks of hallucinations [31], [32]. Personality-based tailoring, after identifying user traits through text-based prompts, could be explored to optimize user interactions. For instance, generative AI systems might adjust their interface to provide enhanced support for users with lower tolerance for errors (e.g., individuals with higher levels of conscientiousness or extraversion) by offering transparent explanations or error-flagging mechanisms [31], [32]. This personalization can improve user engagement and reduce the frustration caused by generative AI hallucinations.

Third, engineering managers can leverage the findings of this research to design targeted training programs that enhance employees' ability to interact effectively with generative AI. These training programs could focus on developing strategies for managing the challenges posed by generative AI hallucinations, particularly for employees with personality traits associated with lower tolerance for hallucinations, such as conscientiousness and extraversion. For instance, training modules could teach employees how to critically evaluate generative AI outputs, identify potential inaccuracies, and incorporate human oversight where necessary. These programs could also provide employees with a deeper understanding of the strengths and limitations of generative AI, enabling them to better align their expectations with the technology's capabilities. Moreover, training could be tailored based on personality insights, ensuring that employees with different traits receive support suited to their needs. For example, individuals with high conscientiousness might benefit from training that emphasizes structured workflows and error-flagging processes to mitigate their discomfort with inaccuracies [73], [89]. Meanwhile, extroverted employees might be guided on managing social implications of using generative AI outputs in collaborative environments [93], [125].

Fourth, engineering managers can use the findings of this research to create diverse teams for tasks involving generative AI. Teams that include individuals with varying levels of agreeableness, openness, conscientiousness, and extraversion can foster a balanced approach to handling generative AI outputs. Such diversity can ensure that while some team members bring creativity and flexibility, others bring critical oversight, enhancing the overall quality of outputs. However, individuals in organizations must be cautious not to over-rely on generative AI as a solution for all tasks [59], [60]. Teams should be encouraged to use human judgment as a complement to AI, ensuring that decisions are not solely based on an imperfect technology.

C. Limitations and Future Research

We acknowledge that this research has some limitations that provide pathways for future research. First, future research can examine the moderating role of situational and contextual factors. In this research, we examine the association between personality traits and tolerance of generative AI hallucinations. Although personality traits offer insights into an individual's attitudes and behaviors through persistent traits [20], scholarly research can benefit by examining the moderating impact of situational and contextual factors on the tolerance of generative AI hallucinations. For example, software developers often have to develop software solutions with a given timeframe and deliver the software with high quality. Therefore, development time and code quality can moderate the relationship between personality traits and tolerance for AI hallucinations in the context of software development. Similarly, in high-stakes contexts, such as healthcare, the potential cost of errors may influence the relationship between individual personality traits and tolerance for AI hallucinations, as users in these contexts may exhibit low tolerance for hallucinations.

Second, future research can examine the robustness of our findings by incorporating additional control variables. In this research, we controlled for age, gender, and education, but did not account for variables such as perceived familiarity with generative AI [126], [127]. We assume that most individuals are familiar with generative AI given its popularity and increasing use [3]. Nonetheless, future research could explicitly control for perceived familiarity to test the robustness of our results.

Third, this study focused on the relationship between individual-level personality traits and tolerance of generative AI hallucinations within the cultural context of the United States. Future research could explore how higher-level constructs, such as organizational and national culture, influence tolerance of generative AI hallucinations by collecting data from different organizations, and cultures [19], [128]. For example, national and organizational cultures in which uncertainty is more acceptable might be more tolerant of generative AI hallucinations compared to cultures that prefer certainty [19].

Fourth, we acknowledge that the scenarios for tolerance of generative AI hallucinations provided in Appendix B.2 focus on contexts that apply to individuals who use generative AI for tasks within and outside organizations. Therefore, future research can develop context-specific scenarios to examine if tolerance of generative AI hallucinations is different for tasks within organizations and outside organizations.

Fifth, future research can examine the relationship between personality traits and the identification of generative AI hallucinations. In this research we examine the relationship between personality traits and the tolerance of generative AI hallucinations. We developed scenarios for tolerance of generative AI hallucinations in Appendix B.2 to indicate that generative AI is hallucinating because we focused on developing a scale to measure tolerance of generative AI hallucinations. However, individuals might not always know whether generative AI is hallucinating or not. Therefore, scholars can examine how personality traits influence identification of generative AI hallucinations.

Sixth, future research can focus on developing more comprehensive measures for tolerance of generative AI hallucinations. In this paper, our focus was on tolerance of generative AI hallucinations as the construct that captures the elements of the user and the system from IS use [105]. However, prior work conceptualizes IS use as comprising three elements: user, system, and task [106], [105]. Therefore, future research can develop richer measures for tolerance of generative AI hallucinations by including the element of the task.

VII. Conclusion

This research examines how individual personality traits are associated with tolerance of generative AI hallucinations. Our findings provide a nuanced perspective on how some individuals are more tolerant of generative AI hallucinations while others are less tolerant. Specifically, individuals high in agreeableness and openness demonstrate greater tolerance for hallucinations. In contrast, those high in conscientiousness and extraversion show lower tolerance. The paper contributes to theory by developing a theoretical framework using Error Management Theory and the Big Five personality traits in the context of generative AI hallucinations. For practice, the results emphasize the importance of designing solutions and training to reduce the adverse impact of generative AI hallucinations and account for diverse user needs and expectations.

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