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# Journal of Information Systems Applied Research and Analytics

# A Proposed Study of Factors Moderating Degree of Trust in LLM and ChatGPT-like Outputs

William Money
wmoney@citadel.edu

Namporn Thanetsunthorn
nthanets@citadel.edu

The Citadel Military College of South Carolina
Charleston, SC 29409

**Abstract**

It is important to understand the human aspect of new AI systems using Large Language Models (LLMs) like ChatGPT and Gemini in our everyday work and how they will influence the processes used to complete our activities and actions. The ways we perceive and interact with these new AI systems using generative technologies are greatly influenced by the trust we place in these technologies. This paper presents a proposed method for investigating the factors influencing the trust individuals placed in the outputs of such system tools, specifically those incorporating Large Language Models (LLMs). These systems and their components possess the capabilities to produce original work that is very highly representative of traditional human made products that reflect but do not simply duplicate the input data by predicting next-word sequences. It is well known that the system outputs may vary with respect to validity and reliability. Ther is a general awareness that a large language model may simply make things up. While traditional research on trust emphasizes interpersonal or interfirm trust, this proposed study will investigate the trust current and potential users place in the LLM technologies, and the factors influencing usage behaviors. Thus, the research aids in the development of a nuanced understanding of why trust is placed in AI LLM products. This understanding is crucial for designing effective tools and frameworks to introduce the tools into organizations. Trust placed in information systems has been found to be important in many domains such as business relationships, work communication, and team interactions. It shapes organizational decisions regarding systems usage. It is important to utilize AI LLM technology's capabilities and functionalities and appreciate that their use and integration into work are mediated by an individual’s trust in this technology as much as one might trust in expert professional skills, and professional competence is important for a specific domain. AI LLM technology trust is therefore differentiated from trust in people to develop a deeper comprehension of users' attitudes and intentions toward this technology’s adoption and usage, facilitating the development of tailored strategies and interventions in information systems research and practice.

**Keywords:** LLM, Trust, ChatGPT, Control, Artificial Intelligence, Credibility.

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# A Proposed Study of Factors Moderating Degree of Trust in LLM and ChatGPT-like Outputs

*William Money and Namporn Thanetsunthorn*

## 1. INTRODUCTION

This paper investigates variables influencing user acceptance and belief in the outputs of ChatGPT like systems using Large Language Models (LLMs). Trust in the outputs of LLMs aids in our understanding of why users may believe and utilize the outputs. The questions broadly consider if the LLMs are viewed as being truthful, accurate, without bias, and correct, or conversely, are they seen as being highly susceptible to hallucinations and prone to creating fiction?

It builds upon the work of McKnight, Carter, Thatcher, & Clay (2011) who previously examined the role of trust within technology systems (Information Systems). They looked at the importance of trust in understanding user interactions with technology. The authors defined trust broadly as the general willingness to rely on a system or entity according to the users' perception. The perceived attributes of ability, benevolence, and integrity were used to evaluate trust in both people and technology. In considering technology trust, the 'ability' refers to perceptions of functional attributes like reliability and performance, while 'benevolence' component of technological trust relates to those that build and support the technology. Although a technology is used, users conceptualization impacts on user behavior.

The value of understanding the circumstances and perceptions associated with trust in technology when it impacts workplace interactions is important. Technology designers and implementors must recognize that users know they must rely on technology's capabilities for effective task performance. This reliance is independent of their trust in the people or the organization behind the technologies (Mcknight, Carter, Thatcher, & Clay (2011).

Mcknight, Carter, Thatcher, & Clay's (2011) work focused on the development and validation of trust technology measures. They noted that there is an important trust impact on technology adoption. It is potentially associated with a technology's acceptance and the user's post-adoption behaviors. Thus, trust influences how users employ a technology after it has been implemented by the organization. This makes trust critical for understanding long-term usage and task and work process dependency.

The research proposed here attempts to fill a gap in the literature by focusing more directly on trust in the technology itself, rather than trust in the human or organizational entities associated with the technology. It will support the development of a more comprehensive explanation of how technological trust influences user behavior and technology acceptance. Results from prior research indicate that trust directly affects user interactions with technology, impacting everything from initial adoption to continued use. It has additional derivative impacts upon user-centric design and user support systems.

Previous research examining trust in technology has distinguished it from trust in the provider of the technology since users might trust the functionality of a software while still being skeptical about the company that produces it. Trust components like system reliability, user support, and perceived utility play critical roles in forming trust in technology itself.

Initial user trust in technology and systems is modeled and analyzed by Li, Hess, Valacich, (2008). They viewed the initial trust as being crucial for overcoming users' initial perceptions of risk and uncertainty when adopting new technologies. Their research suggests that initial trust forms because users must rely on secondary information and preconceived expectations about a technology's characteristics before actual use. Indirect information such as the technology's perceived attributes, strong organizational backing, and societal endorsements shape and form the users' attitudes and subsequent decisions to adopt and trust in the technology.

Personality factors, cognitive assessments of the technology's reliability and effectiveness, calculative judgments on the benefits versus risks, and institutional factors prompt initial trust assessments (Li, Hess, & Valacich, 2008). These elements collectively contribute to initial trusting beliefs and intentions. Organizations that seek to build positive user first impressions and encourage technology gain value from understanding how these first impressions are formed. They may then improve adoption, and more effectively direct initial user perceptions.

The impact of interacting with ChatGPT, a language model developed by OpenAI, has been assessed previously by examining its relationship with trust, user perception, stereotype perception, and two psychological outcomes: self-esteem and psychological well-being (Salah, Alhalbusi, Ismail, & Abdelfattah, 2023). The research study hypothesizes that there is a positive direct relationship between trust in ChatGPT, user perception, and stereotype perception of ChatGPT with self-esteem. Job anxiety was also hypothesized to be a moderator of the relationship between user perception of ChatGPT and psychological well-being. Stereotyped perceptions of ChatGPT were found to significantly predict self-esteem, while user perception and trust in ChatGPT had a positive direct relationship with self-esteem based on this work. Job anxiety moderates the relationship between user perception of ChatGPT and psychological well-being. The hypothesized psychological effects of AI technology are supported by these data.

Users have reason to mistrust generative models according to research on these tools. Their tendency to "hallucinate" or make up responses and generate outputs that are biased or may contain harmful content has been described in many publications and blogs. Schulman, Zoph, Kim, Hilton, Menick, Weng, J., ... & Ryder (2022) trained a ChatGPT model and described a number of potential problems with the output. These included: ChatGPT sometimes writes apparently plausible-sounding but incorrect or nonsensical answers; declines responding to questions that it could answer correctly; ChatGPT responses are sensitive to tweaks to the input phrasing or attempting the same prompt multiple times with is answering correctly or incorrectly based on prompt variations; it often excessively verbose and overuses certain phrases and over-optimization; does not ask clarifying question and usually guesses what the user intended; and will sometimes respond to harmful instructions or exhibit biased behavior.

For example, Alkaissi, & McFarlane (2023) instructed ChatGPT to write about the pathogenesis of two conditions - homocystinuria-associated osteoporosis, and a rare metabolic disorder, late-onset Pompe disease (LOPD). The results found negative aspects of the chatbot's performance. Comparing it to the US Medical Licensing Examination (USMLE) Step 1, Step 2 CK, and Step 3, as open-ended and multiple-choice questions (MCQ). The result showed the accuracy was low indicating that the performance is tied to perception and understanding of the subject. The authors note that the written outputs are credible, but that generated data mixes true and completely fabricated data,

## 2. RELATED WORK

**Trust**

The literature on trust and automation systems suggests that LLMs may be subject to moderation by several variables that would both promote or discourage trust and therefore influence the user's action regarding the outputs of an LLM. The user might have a tendency to disregard the model's response or question the outputs of these systems or conversely accept the results without checking the facts against known values or original reputable sources.

The issues with trust in LLM and ChatGPT like output is significant for many reasons (Brzowski, & Nathan-Roberts, November 2019). The authors argue that a lack of human users' trust is due to the limited semantic understanding between humans and similar systems. They posit that the communication between the user and the LLMs, such as ChatGPT, may be used to develop greater degrees of trust because they offer an interactive collaboration approach. The authors assessed the impact of ChatGPT on trust in a human-robot collaboration assembly task. A robot control system used ChatGPT to control a 7-degree-of-freedom robot arm. The arm retrieved and placed tools using natural language control issues by humans. The user's trust measured by attitude surveys was increased. This was attributed to the Chatbot understanding the nuances of human language and responding appropriately. The findings of this study suggest that the development of trust can be improved after experience and with positive results.

The value of trust in technology and especially new technologies such as LLMs has long been a topic of study int the information systems literature. Trust has been examined in the information systems domain. It has been shown to be important in explaining the adoption and use of new technologies such as the usage of systems in e-commerce, and virtual communities (Söllner, & Leimeister, 2013). These authors examined a body of knowledge on trust regarding its reliability and the antecedents of trust in the information systems literature. They examined many different antecedents for different trust relationships in different contexts. They found that measurement model mis-specification issues could be serious challenges in information systems trust research. The most common issue involved using formative indicators in reflective measurement models. This could threaten the strength of the association found in the structural relationships between trust and its antecedents in these studies.

Lowry et al. (2008) and Vance et al. (2008) research addresses measurement model mis-specification and the use of second-order measurement models to assess the trust in systems. These researchers report that the work by (Klein & Rai, 2009; Venkatesh & Bala, 2012) was valuable and solid. Klein, & Rai (2009) found that trust was very important as an aid in strategic information flows between buyers and suppliers within logistics supply chain relationships. It positively impacted other relationship-specific performance outcomes. Trust results in the valuable development of cooperative initiatives and relationships rather than conventional “arms-length” transactional exchanges. The partnerships are not limited to the sharing of order-related information and extend to strategic information that has value for both parties. The Venkatesh, & Bala (2012) research on the inter-organizational business process standards (IBPS) found the standards are adopted because of trust factors that represent synergies between a focal firm and its trading partners. Their study of 248 firms (124 dyads) in the high-tech industry also found that relational trust had direct effects on IBPS adoption.

Salah, Alhalbusi, Ismail, & Abdelfattah (2023) investigated generative AI tool adoption (ChatGPT and Bard) in public administration and street-level bureaucracy. They identify several benefits from the use of these powerful tools including insights into bureaucratic behavior and decision-making processes, and citizen interactions. However, they also recognize that the complex nature of AI algorithms (such as those applied by ChatGPT) poses difficulties for researchers' and stakeholders' comprehension of the decision-making processes behind AI-generated insights. Concerns about accountability and trust in AI-driven research findings may result from this lack of algorithmic transparency. They recommend that clear explanations of the AI algorithms and their implications be provided with the outputs.

**Self Efficacy**

Self-efficacy has been shown to be associated with and an influencer of trust in a variety of commerce and technology situations. Trust has been recognized as a critical factor for electronic commerce because online transactions are characterized as a process that involves uncertainty and risk. Achieving a high degree of trust is an effective means of reducing uncertainty and risk. Kim, & Kim (2005, January) research describe self-efficacy as having an impact on trust building and uncertainty reduction. The results show that self-efficacy affects trust in the web vendor and positively influences purchase intentions.

Abdunabi, Hbaci, Center, & Nyambe (2023) examined perceived programming self-efficacy of information system students as a factor helping students learn to program. Their examination of students' internal characteristics and programming self-efficacy found a strong connection. Their survey assessed students' beliefs in their programming competence, value attributed to learning programming, time spent practicing, and instructional guidance frequency. The value students placed on learning programming was described as the most significant variable associated with programming self-efficacy.

Internet banking (IB) has also been investigated as an outcome impacted by four factors - hedonic motivation, habit, self-efficacy and trust using a survey questionnaire that collected data for structural equation modelling (SEM). These research findings strongly supported the conceptual model by explaining 73% of variance in behavioral intention to use internet banking (Alalwan, Dwivedi, Rana, Lal, Williams, 2015). Further, hedonic motivation, habit, self-efficacy and trust are all confirmed to have significant influences on behavioral intention. Trust was found to be profoundly predicted by both self-efficacy and hedonic motivation.

Chamorro-Koc, Peake, Meek, & Manimont (2021) researched the growing commercial market for wearable health technology. But they value is questioned by their work due to the lack of validation and abandonment rates. Self-efficacy mechanisms are being incorporated into the design of health technologies, through (i) past experience, (ii) tracking of activities , (iii) autonomy, (iv) strong interest in personal health, and (v) reliability and validity of data impacts on confidence in health technologies. Their conceptual model offers support for improving self-efficacy and trust in health technologies so designers and developers can incorporate these factors into design features for effective personal health technology.

Perceived Control. Humans and intelligent agent interactions are very important in today's world because of the large number of services and controls that are available to individual management. Research on human agent interaction (HAI) has therefore become important since effectively controlling the agents can improve efficiency and interactions. Liao, Li, Cheng, & Yang (2023) assert that at some point human will have negative emotions (toward agents) such as panic, fear, and disgust of the very effective. The study defines perceived control as the degree of confidence people have in interacting with intelligent agents. It is seem as an overall evaluation and attitude of intelligent agents' feeling of control. Thus, high perceived control of intelligent agents is a good description of a desired human relationship with HAI. Perceived control represents a sense of internal control based on the ability, knowledge, skills, or familiarity that produces cognitive and decisional control.

Technology Acceptance Model (TAM). Decisions regarding the acceptance or rejection of new technology have open question as new systems and technologies have had greater and greater impacts upon people's lives and work environments. The reasons behind acceptance and the factors that influence acceptance have been assessed with the technology acceptance model (TAM) for approximately 35 years. The model stems from the psychological theory of reasoned action and theory of planned behavior. It has aided greatly in our understanding of the predictors of human behavior toward prospective acceptance or rejection of a technology. The model has been extended and modified to apply to a variety of information systems and related technologies. The body of research has revealed new factors that can significantly influence the TAM core variables Holden,& Karsh (2010). TAM is understood to contain six causally related constructs: perceived ease of use, perceived usefulness, attitude towards using, behavioral intention to use and actual system use (Davis, Bagozzi & Warshaw, 1989; Erasmus,, Rothmann, & Van Eeden, 2015).

Trust has been found to be an important concept that can be integrated with TAM. For example, Pavlou's (2003) research applied the TAModel variables (perceived usefulness and ease of use) to a technology-driven environment to predict e-commerce acceptance. Paviou integrated trust and perceived risk (uncertainty of the environment) with TAM. The research findings strongly support the proposed model, showing that trust was an indirect antecedent acting through risk perception. Additionally, research by Wu, Zhao, Zhu, Tan, & Zheng (2011) identified trust as an important factor that influences the user's online behavior. This role of trust on subject type (students or non-students) and context type (commercial or non-commercial) significantly influenced TAM constructs.

## 3. RELEVANT CONTROL VARIABLE

**Demographic Factors**.
Trust in e-vendors and their technologies implemented through IT and Web site interfaces is a multifaceted construct influenced by various factors (Gefen et al., 2003). Building upon previous research, scholars have explored and identified numerous factors as significant predictors of individuals' propensity to trust in technologies (including systems like ChatGPT). Thus, it is essential to consider these variables as control variables when conducting surveys to measure the level of trust in technologies. This approach can effectively isolate the potential influence of specific factors, thereby yielding a more accurate understanding of users' attitudes regarding trust in technologies. Notably, demographic factors and individual differences in personality traits emerge prominently among the factors contributing to trust in technologies (e.g., Choung et al., 2023; McElroy et al., 2007; Sundar, 2020; Svendsen et al., 2013; Venkatesh et al., 2003).

Regarding demographic variables such as age, gender, level of education, and socioeconomic status, there is a general consensus among researchers that including these variables in surveys allows for a better understanding of how trust in technology varies across different demographic groups and population segments (Gefen et al., 2003; Venkatesh et al., 2003). In particular, previous research examining technology acceptance models has documented that age plays a crucial role in how people adopt technologies and trust automation (e.g., Hoff & Bashir, 2015; Morris & Venkatesh, 2000). For example, older individuals tend to prefer human editors over balancing algorithms for news story consumption (Thurman et al., 2019). They also tend to be more skeptical than younger people about the fairness of decisions made by automation, robots and AI (Hoff & Bashir, 2015; Oksanen et al., 2020). This difference may be attributed to varying levels of familiarity and comfort with technology, with younger individuals, who are more exposed to and familiar with technology, showing higher levels of trust (Morris & Venkatesh, 2000).

There have been scholarly efforts dedicated to investigating whether gender is a significant predictor of the use of AI tools and how perceptions of AI tools vary by gender. Previous research consistently shows that gender influences how individuals interact with AI technologies. For example, women are often perceived as underrepresented in the fields of technology with a study of social robot use (De Graaf & Allouch, 2013). They are also shown to be under-represented as users and creators in using AI-based tools in a STEM study of women. The study found they are thereby limited (by gender) in their access to and utilization of AI tools (Ofosu-Ampong, 2023). Gender differences can also reveal varying perceptions and attitudes toward new technology (Venkatesh & Davis, 1996; Venkatesh & Morris, 2000). In their seminal work, Venkatesh and Morris (2000) conducted a five-month survey involving 342 workers regarding the transition to a new software system. The survey results indicate that men tend to base their technology usage decisions more heavily on perceived usefulness compared to women. Conversely, women are more influenced by perceptions of ease of use and social norms.

In addition to age and gender, levels of education and socioeconomic status are widely recognized as significant factors influencing the level of trust individuals place in technologies. Previous research suggests that higher levels of educational attainment are often linked to greater critical thinking skills and a better understanding of complex technologies, leading to more informed and nuanced trust in social networking sites (Hargittai & Hsieh, 2010), Internet usage types (Van Deursen & Van Dijk, 20140, and AI in medicine for radiology, robotic surgery, and dermatology (Yakar et al., 2022). Specifically, individuals with higher education levels are more likely to utilize AI technologies and make informed judgments about their reliability and benefits. Similarly, socioeconomic status can influence trust in AI by affecting access to technology and related resources. Individuals with higher incomes often have greater exposure to and familiarity with advanced technologies, which can cultivate a more trusting attitude toward AI (Van Deursen & Van Dijk, 2014; Zhang & Dafoe, 2019). These individuals are also more likely to experience the benefits of AI in their daily lives, subsequently reinforcing their trust in AI technologies. On the other hand, those with lower socioeconomic status may have limited access to technology, leading to less familiarity and potentially more skepticism about AI technologies. The significance of education level and socioeconomic status in shaping perceptions and acceptance of AI technologies is further highlighted in the work of Choung et al. (2023). Their survey of 525 respondents from the general U.S. population demonstrates that adults with higher levels of education and income tend to exhibit greater trust in AI.

**Personality Traits**

Human-related factors beyond demographics are widely recognized as critical determinants of individuals' technology trust and Internet use (McElroy et al., 2007), human-AI interaction (Sundar, 2020), and consumer use of technology (Venkatesh, Thong, & Xu, 2012). This body of literature predominantly focuses on the Five-Factor Model of personality traits, commonly known as the Big Five, which encompasses agreeableness, openness, conscientiousness, extraversion, and neuroticism (Digman, 1990; John et al., 2008). The model has been a focal point in the existing literature for evaluating how personality traits may influence individuals' willingness to trust in technologies. Numerous studies utilizing the Big Five have demonstrated that these traits can significantly impact individuals' trust in technologies, underscoring the importance of considering personality when developing designs for technologies and when implementing systems. Below, we discuss some notable studies in this area.

The majority of previous studies indicate a positive correlation between agreeableness and trust in human-centered AI interfaces (Böckle et al., 2021), technology acceptance (Devaraj et al., 2008), and trust in automated vehicles (Kraus et al., 2020). In their influential work, Park and Woo (2022) investigated affective and cognitive attitudes toward AI. They found that individuals with high agreeableness scores tend to hold positive attitudes toward AI, particularly regarding its perceived usefulness. Similarly, consistent research findings indicate that individuals with high levels of openness tend to exhibit favorable attitudes toward AI. For example, Antes et al. (2021) conducted research on attitudes toward AI driven healthcare technologies, and Oksanen et al. (2020) have reported evidence from an online AI trust game that openness to experience is strongly correlated with greater trust in AI systems. Their work supports a previous DeYoung et al. (2007) finding that individuals with high levels of openness are more likely to seek out new information and experiences. This propensity for exploration and curiosity likely contributes to individuals' higher levels of trust and acceptance of new technologies (McElroy et al., 2007; Svendsen et al., 2013).

The literature also indicates that extraversion and conscientiousness play significant roles in shaping individuals' trust in machine characteristics and auto use (Merritt & Ilgen, 2008), AI based voice technologies (Bawack et al., 2021), and in AI voice shopping (Kraus et al., 2020). Extraverts, characterized by their sociability and enthusiasm, are more likely to adopt AI-driven systems, such as robots and virtual assistants, due to their preference for social interaction (Kaplan et al., 2019; Oksanen et al., 2020). Similarly, conscientiousness, which reflects traits such as diligence and carefulness, has been found to correlate positively with trust in cloud customer relationship management technology by Fu, & Chang (2016). This finding support the position that conscientious individuals tend to value the reliability and efficiency of information systems, resulting in higher levels of trust in these technologies. McKnight et al. (2002) further argue that the methodical and organized nature of conscientiousness aligns well with the structured and predictable aspects of information systems. This alignment implies that conscientious individuals are more likely to trust technology due to their propensity to appreciate the reliability and consistency that information systems offer. On the other hand, individuals with lower levels of neuroticism, which indicates emotional stability, tend to be more accepting of technology. Prior studies show that individuals scoring low on neuroticism tend to experience less anxiety and distrust, leading to a more positive attitude toward AI technologies (Kraus et al., 2020; Sharan & Romano, 2020, Zhang et al., 2020). This reduced anxiety enables them to engage more confidently with AI systems, thereby enhancing their trust in such technologies.

## 4. CONCEPTUAL FRAMWORK

Our research framework is based upon the psychological theories of reasoned action and theory of planned behavior as is the TAM body of research. We seek to expand our understanding of the role of trust from the perspective of the individual, and our appreciation of the important role that predictors of human trust in LLM and AI technology. (Holden,& Karsh (2010); Davis, Bagozzi & Warshaw, 1989; Erasmus,, Rothmann, & Van Eeden, 2015).

## 5. METHODOLOGY

We developed the following 5 primary hypotheses for this study based in the trust literatures suggesting propensities to trust in the AI LLM technology, and the related literature.

H1. Perception of High self-efficacy will positively impact the level of Trust in LLMs.
H2. Perception of High-Control will positively impact the level of Trust in LLMs.
H3. Perception of High-Usefulness will positively impact the level of Trust in LLMs.
H4. Perception of High Ease of Use will positively impact the level of Trust in LLMs.
H5. High Intention to Use will positively impact the level of Trust in LLMs.
H6. Control Variable will show significant differences in intention to use and use of AI ChatGPT technologies among sub-populations.

Data for this research will be collected with a survey questionnaire administered to graduate and undergraduate students in the summer and fall semesters, 2024. (The number of participants will depend upon enrollment and sections participation.) It is important to note that the researchers expect the graduate and undergraduate classes to have significant difference when categorized by the control variables. The graduate students are primarily part-time and employed. The undergraduates are younger (compared to the graduates), full time, unemployed, and with little or no earned income. The respondents' demographics (ages ranges, sex, education levels, etc.) will be reported and used in the analyses.

The students will be asked to offer response with and about their trust and their use of using an LLM or ChatGPT like system. Students will be provided a link to the survey questionnaire randomly distributed using MS Forms.

SPSS application (Version-20) or SAS 9.4 was used to analyze the data. The instrument used for this study was designed based on the focus of trust, the investigation objective of the study. The reliability and validity of the instruments will be calculated and reported.

Survey data were collected using a five-point Likert scale (1 for strongly disagree to 5 strongly agree). The survey question are adapted from existing survey scales from prior research. The survey guidance will state that the questionnaire investigates students' opinions about their trust in the use of ChatGPT and other LLMs.

The survey questions are show in the appendix.

## 6. DISCUSSION

We recognized there will be several important limitations to this work. First, this study only addresses generative AI LLMs, and only one specific tool (ChatGPT) will be referred to in the survey questionnaire. Thus, the results may not be widely transferable, and other forms of generative technology (RAG -Research Augmented Generation), and other tools that may be used by the respondents. Secondly, the trust measures may have different meanings for different populations. Trust, due to one's inherent belief in technology, may vary based on the task performed and the situation or context of the work. The student sample used to collect the data may not represent a more general population and may not address the context and nuances of the situations where AI and GPT is eventually employed. Finally, the student population may not effectively represent the organization member who is to use and apply AI in a work environment.

Unfortunately, we have no hard measures to compare our result with actual access and use of AI and ChatGPT in producing work products. We believe would be informative to know if individuals are actually using the LLMs, and the extent of the usage and reliance on these products.

## 7. CONCLUSIONS

Our conclusion will depend upon the study results and detailed analysis of trust and the control variables. However, we believe there is no question that AI and Chat like LLMs may add great value and save user time for some tasks. They are and will be used by organizations and the public to for work productivity improvements. We hope to help answer important questions - who will place trust in the output of these tools and use them in important or valued work? Does trust in AI and specifically ChatGPT like products compare favorably with existing models describing continued postadoption of its use. Significant questions for additional research will exist after our work. For example, does the influence of trust in this new AI vary over time? Will belief in technology improve as the products mature and evolve to provide new features, and how will product evolution take to impact adoption behavior? Finally, future work may help to determine if trust in AI may mediates the influence of trust in people who promote, develop, or support a specific AI product. Conversely, it is not clear if trust in AI and ChatGPT like successes can influence trust in people to build or deploy the technology? Our future research will explore these questions.

## 8. RECOMMENDATIONS

Our recommendation for the users, designers, developers and LLM technologies will be based upon our findings and discussion of the issues associated with this new technology..

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## Appendix 1 (Qualtrics Survey)

Survey questions are provided in this appendix.
These questions have been carefully reviewed and rewarded as appropriate by replacing the "system" terminology with "LLM or chat GPT like" system designation for clarity in the appropriate questions. The survey is currently complete in Qualtrics.

Survey Introduction

Welcome to our new technology survey!

> This survey aims to gather feedback and insights on the user experience and perceptions of the Large Language Model (LLM) or ChatGPT like system. Even if you have not tried or used an LLM, we would like you to share your thoughts about this new technology.
>
> The LLM is an advanced language model that uses artificial intelligence (AI) technology to generate human-like text responses based on users' queries or prompts. It can engage in conversations, answer questions, provide explanations, and generate creative content across a wide range of topics. ChatGPT, created by OpenAI, is one example of the LLM.
>
> Your feedback is valuable in helping us understand how users interact with and perceive this cutting-edge technology. Your responses will always remain anonymous and confidential.
>
> Thank you for taking the time to participate in our survey!

Demographic Questions (Select appropriate category)

Age, Gender, Level of Education, Employment Status (student – not employed. Student -employed - FT), Household Income (and N/A), Ethnicity/Race, Marital Status, Number of Children

Use and Knowledge of LLMs (Like ChatGPT)
- I have never Hear of this technology.
- I have heard or read about it but have not used it yet.
- tried it once or twice – free versions.
- I use it infrequently (every 3-4 months).
- I use it monthly.
- I use it weekly.
- I use it daily.
- I use it very often each day.
- I have purchased a subscription and pay for its use. (Yes, No.)

Likert Scale:

1 = Strongly agree, 2 = Agree, 3 = Neutral, 4 = Disagree, 5 – Strongly agree

Personality

Personality (I see myself as: )
Someone who is reserved.
Someone who is generally trusting.
Someone who tends to be lazy.
Someone who is relaxed, handles stress well.
Someone who has few artistic interests.
Someone who is outgoing, sociable
Someone who tends to find fault with others.
Someone who does a thorough job.
Someone who gets nervous easily.
Someone who has an active imagination.

Trust questions (Madsen, & Gregor, 2000)

R1 - The system always provides the advice I require to make my decision.
R2 - The system performs reliably.
R3 - The system responds the same way under the same conditions at different times.
R4 - I can rely on the system to function properly.
R5 - The system analyzes problems consistently.

2. Perceived Technical Competence
T1 - The system uses appropriate methods to reach decisions.
T2 - The system has sound knowledge about this type of problem built into it.
T3 - The advice the system produces is as good as that which a highly competent person could produce.
T4 - The system correctly uses the information I enter.
T5 - The system makes use of all the knowledge and information available to it to produce its solution to the problem.

3.Perceived Understandability
U1 - I know what will happen the next time I use the system because I understand how it behaves.
U2 - I understand how the system will assist me with decisions I have to make.
U3 - Although I may not know exactly how the system works, I know how to use it to make decisions about the problem.
U4 - It is easy to follow what the system does.
U5 - I recognize what I should do to get the advice I need from the system the next time I use it.

4. Faith
F1 - I believe advice from the system even when I don’t know for certain that it is correct.
F2 - When I am uncertain about a decision I believe the system rather than myself.
F3 - If I am not sure about a decision, I have faith that the system will provide the best solution.
F4 - When the system gives unusual advice I am confident that the advice is correct.
F5 - Even if I have no reason to expect the system will be able to solve a difficult problem, I still feel certain that it will.

5. Personal Attachment
P1 - I would feel a sense of loss if the system was unavailable and I could no longer use it.
P2 - I feel a sense of attachment to using the system.
P3 - I find the system suitable to my style of decision making.
P4 - I like using the system for decision making.
P5 - I have a personal preference for making decisions with the system.

Perceived Control Questions

Perceived Control. Liao, Li, Cheng, & Yang (2023) The scale includes affective control, cognitive control and conative control .

Affective control
(F1) AC1 The intelligent agent is always trying to entertain me.
AC2 The intelligent agent is very polite to me.
AC3 The intelligent agent only cares about me.
AC4 The intelligent agent does not get angry.
AC5 The intelligent agent makes me feel superior.

Cognitive control
CgC1 Human beings dominate the intelligent agent.
CgC2 I understand how the intelligent agent works well.
CgC3 The intelligent agents are designed to serve us.
CgC4 I know how to use intelligent agents very well.

Conative control
CaC1 I can dictate the behavior of intelligent agents.
CaC2 The intelligent agent obeys me.
CaC3 The intelligent agent only acts when I allow it.

Self-Efficacy (Schwarzer, 1992).

1 I can always manage to solve difficult problems if I try hard enough.
2 If someone opposes me, I can find the means and ways to get what I want.
3 It is easy for me to stick to my aims and accomplish my goals.
4 I am confident that I could deal efficiently with unexpected events.
5 Thanks to my resourcefulness, I know how to handle unforeseen situations.
6 I can solve most problems if I invest the necessary effort.
7 I can remain calm when facing difficulties because I can rely on my coping abilities.
8 When I am confronted with a problem, I can usually find several solutions.
9 If I am in trouble, I can usually think of a solution.
10 I can usually handle whatever comes my way.

**Namporn - TAM Questions** (modified from Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly*, 13(3), 319-340.)

**Perceived Usefulness:**
1. Using AI technologies enable me to accomplish tasks more quickly.
2. Using AI technologies improve my job performance.
3. Using AI technologies increase my productivity.
4. Using AI technologies enhance my effectiveness on the job.
5. Using AI technologies make it easier to do my job.
6. I find AI technologies useful in my job.

**Perceived Ease of Use:**
1. It is easy for me to learn how to use AI technologies.
2. It is easy for me to make AI technologies do what I want them to do.
3. I find my interaction with AI technologies is clear and understandable.
4. I find AI technologies to be flexible to interact with.
5. It is easy for me to become skilled in using AI technologies.
6. I find AI technologies easy to use.