

**EFFECTS OF INDIVIDUAL DIFFERENCES IN PERSONALITY TRAITS AND
SELF-CONCEPT OF ABILITIES ON WILLINGNESS TO ADOPT AI TOOLS**

A Dissertation
Presented to
The Academic Faculty

By

Lucas Evan Provine

In Partial Fulfillment
of the Requirements for the Degree
Master's of Science in the
School of Psychology

Georgia Institute of Technology

May 2024

© Lucas Evan Provine 2024

**EFFECTS OF INDIVIDUAL DIFFERENCES IN PERSONALITY TRAITS AND
SELF-CONCEPT OF ABILITIES ON WILLINGNESS TO ADOPT AI TOOLS**

Thesis committee:

Dr. Ruth Kanfer, Advisor
School of Psychology
Georgia Institute of Technology

Dr. Phillip Ackerman
School of Psychology
Georgia Institute of Technology

Dr. Rickey Thomas
School of Psychology
Georgia Institute of Technology

Date approved: March 12, 2024

ACKNOWLEDGMENTS

There are several individuals without whom this milestone could not have been achieved. First, I would like to express my gratitude to my thesis committee. I am immensely thankful to Dr. Ruth Kanfer, Dr. Phillip Ackerman, and Dr. Rick Thomas for their time spent providing me with guidance, feedback, and insight to improve my work and academic development. I would also like to highlight my appreciation to Dr. Kanfer and Dr. Ackerman for providing me with additional financial support to meet my sample size.

I wish to thank my parents for their endless love and support. They have instilled in me the determination and tools to continuously improve. I cannot stress enough how fortunate I am to have them as parents, and this accomplishment is as much theirs as it is my own.

To my dearest friends and loved ones, who have provided me with emotional support and companionship. Your faith in my abilities keep me motivated.

TABLE OF CONTENTS

Acknowledgments	iii
List of Tables	viii
List of Figures	x
List of Acronyms	xi
Summary	xii
Chapter 1: Introduction	1
1.1 Background	1
1.2 Purpose	4
Chapter 2: Literature Review	6
2.1 Artificial Intelligence	6
2.1.1 AI and Decision-Making	7
2.1.2 Problematic Characteristics of AI	8
2.2 Personality	9
2.2.1 Five-Factor Model	10
2.2.2 Tellegen’s Model	11
2.3 Self-Concept of Ability	11

2.4	Propensity to Trust	13
2.5	Technology Acceptance Models	14
2.5.1	Unified Theory of Acceptance and Use of Technology (UTAUT)	14
2.5.2	Personality, Self-Concept, and Technology Acceptance	16
2.6	The Present Study	18
2.6.1	Hypotheses	19
Chapter 3: Method		23
3.1	Participants	23
3.2	Materials and Measures	24
3.2.1	UTAUT Construct Measures	24
3.2.2	Five-Factor Model Personality Measures	26
3.2.3	Tellegen’s Model of Personality Measures	26
3.2.4	Propensity to Trust	26
3.2.5	Self-Concept of Abilities	27
3.2.6	Demographic Variables	27
3.2.7	Trait-Matched AI Adoption Vignettes	28
3.3	Procedure	28
Chapter 4: Results		30
4.1	Data Cleaning Procedure	30
4.2	Descriptive Statistics	30
4.3	Hypothesis Testing	30
4.3.1	Hypothesis 1 Results	31

4.3.2	Hypothesis 2 Results	35
4.3.3	Hypothesis 3 Results	36
4.4	Exploratory/Supplementary Analyses	47
4.4.1	Perceptions of Liability	47
4.4.2	Individual Differences as Distal Predictors	48
4.4.3	Behavioral Intention Responses to Individual Vignettes	52
Chapter 5:	Discussion	58
5.1	Interpretation of Results	58
5.1.1	Individual Differences and Adoption Intentions	58
5.1.2	Personality and Attitudes	59
5.1.3	Self-Concept and Attitudes	60
5.1.4	Situational Influence of Perceived Liability	61
5.1.5	Individual Vignette Characteristics and Behavioral Intentions	61
5.1.6	Limitations	62
5.1.7	Theoretical Implications	63
5.1.8	Practical Applications	64
5.1.9	Future Directions	65
5.1.10	Conclusion	66
References	69
Appendices	78
Appendix A:	UTAUT 2 Measure Modified for AI Context (Venkatesh et al., 2012)	79

Appendix B: IPIP Scales Measuring Constructs Similar to NEO-PI-R: Neuroti- cism & Extraversion	81
Appendix C: Tellegen’s Multidimensional Personality Questionnaire (MPQ): So- cial Potency and Social Closeness Measures	84
Appendix D: Propensity to Trust Measure	85
Appendix E: Academic Self-Concept Measure	86
Appendix F: Demographic Questionnaire Items	87
Appendix G: AI Adoption Vignettes	88
Appendix H: Commitment and Effort Check Questions	93

LIST OF TABLES

3.1	Descriptive Statistics for Demographic Variables	25
4.1	Descriptive Statistics for Hypothesized Variables	31
4.2	Descriptive Statistics for Hypothesized Variables	32
4.3	Multiple Linear Regression of Personality Variables Predicting Behavioral Intentions	33
4.4	Hierarchical Regression of Personality's Increment Over UTAUT	34
4.5	Multiple Linear Regression of Self-Concept Variables Predicting Behavioral Intention	35
4.6	Hierarchical Regression of Personality's Increment Over UTAUT	36
4.7	Simple Linear Regression of Extraversion Predicting Matched Behavioral Intentions	37
4.8	Hierarchical Regression for Extraversion-Matched Vignettes	39
4.9	Simple Linear Regression of Neuroticism Predicting Matched Behavioral Intentions	39
4.10	Hierarchical Regression for Neuroticism-Matched Vignettes	40
4.11	Simple Linear Regression of Verbal Self-Concept Predicting Matched Behavioral Intentions	41
4.12	Hierarchical Regression for Verbal-Matched Vignettes	42
4.13	Simple Linear Regression of Math Self-Concept Predicting Matched Behavioral Intentions	42

4.14 Hierarchical Regression for Math-Matched Vignettes	43
4.15 Simple Linear Regression of Spatial Self-Concept Predicting Matched Behavioral Intentions	44
4.16 Hierarchical Regression for Spatial-Matched Vignettes	45
4.17 Simple Linear Regression of Organizational Self-Concept Predicting Matched Behavioral Intentions	45
4.18 Hierarchical Regression for Organizational-Matched Vignettes	47
4.19 Hierarchical Regression for Organizational-Matched Vignettes	48
4.20 Hierarchical Regression Predicting Performance Expectancy	50
4.21 Hierarchical Regression Predicting Effort Expectancy	51
4.22 Hierarchical Regression Predicting Social Influence	51
4.23 Descriptive Statistics for Vignette BI Responses	53
4.24 Correlation Table of Behavioral Intention Responses by Vignette	54
4.25 2-Factor EFA with Quartimax Orthogonal Rotation	55
4.26 Vignettes Grouped by Identified Composite Factors	56
4.27 Bivariate Correlations of Predictor Variables and Behavioral Intention Composite Variables	57

LIST OF FIGURES

3.1	Procedure Order and Measures	29
-----	--	----

SUMMARY

Artificial intelligence (AI) is increasingly being used to automate and augment tasks in a variety of domains from the workplace to daily life. However, little is known about the influence that individual differences in personality and ability self-concept have on people's attitudes and adoption of AI technology to assist with tasks. The objective of this study was to determine how select personality traits (e.g., extraversion, neuroticism, and propensity to trust) and ability self-concept (e.g., verbal, math, spatial, and organizational) contribute to one's willingness to adopt AI for decision-making purposes in various contexts. I leveraged the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) to do so. To accomplish this, 231 working adults (126 females and 105 males) were recruited from Prolific to participate in a vignette study that involved the assessment of attitudes and behavioral intentions to use AI in 22 scenarios. The results indicated that: (1) the personality and self-concept variables do not contribute additional meaningful variance in predicting behavioral intentions to use AI over and above UTAUT's performance expectancy, effort expectancy, and social influence variables; (2) one's general propensity to trust others is associated with more positive expectations of AI performance; (3) higher ability self-concept is positively associated with perceiving AI as requiring less effort to use; and (4) attitudes and intentions toward using AI are significantly lower when individuals perceive personal situational liability for the consequences of errors that might occur while using the AI. Future researchers are encouraged to further explore how salient situational factors and stable individual difference variables might interact to inform people's attitudes and intentions toward using AI.

CHAPTER 1

INTRODUCTION

1.1 Background

Artificial intelligence (AI) is increasingly being used to automate and augment daily processes such as decision-making, problem-solving, and creative endeavors (Benbya et al., 2020). Consider the impact of Chat General Pre-Trained Transformer (i.e., ChatGPT) a conversational generative AI developed by OpenAI in November of 2022 that uses a complex language model to respond to natural language inputs (OpenAI, 2023). While it has its limitations, this model can perform a staggering number of knowledge tasks such as writing essays, emails, poems, screenplays, debugging code, and so on, with a few user-entered prompts. However, the quality and accuracy of its outputs can be dubious, with OpenAI clearly stating that, “ChatGPT can make mistakes. Consider checking important information.” (OpenAI, 2023). As AI continues to be incorporated into facets of daily life including the workplace, the likelihood that the average individual will have the opportunity to use or even rely on an AI tool for tasks increases. Just as AI can suggest an efficient route via Google Maps or the next show to watch, AI can make suggestions relevant to job tasks (Carpenter, 2019), and when it comes to incorporating this technology into the workplace, AI has considerable potential to augment some job tasks in a way that improves efficiency and reduces cognitive workload for employees.

Despite the benefits and potential that AI poses for a technologically advanced society, it is apparent that AI is not universally accepted when it comes to having a stake in making decisions. Surveys and research studies consistently report that people’s attitudes toward applications of AI are mixed and that not everyone is willing to take advice from machines. For example, a 2019 report from the Future of Humanity Institute at the University of

Oxford surveyed a diverse sample of adults in the U.S. with ages ranging from 18 to older than 73 to examine attitudes and beliefs about AI. The results of this survey showed that 41% of Americans somewhat support or strongly support the development of AI in general while 22% somewhat oppose or strongly oppose it (Zhang & Dafoe, 2019).

This phenomenon has also been empirically examined in a research stream examining people's acceptance of human advice compared to advice from algorithms (see review by Jussupow et al., 2020). Furthermore, general aversion toward AI echoes Meehl's (1954) work on clinical versus statistical prediction. He aimed to better understand the relative accuracy of statistical procedures to clinical judgments and found that statistical prediction consistently outperformed clinical judgment. Despite this, Meehl observed that people tended to show a preference for the lower accuracy of clinical judgment given by human experts. This work is often referenced in more contemporary research examining a similar phenomenon. Dietvorst and colleagues (2014) coined the term "algorithm aversion" to indicate a phenomenon where users more often rely on human advice than advice from a statistical algorithm. Contrary to Dietvorst's findings, other researchers have examined the opposite phenomenon in which users prefer the advice from algorithms over humans in some circumstances and dubbed, "algorithm appreciation" (Logg et al., 2019), further emphasizing a gap in how AI is perceived. It should be noted here that while not all algorithms should be considered AI, AI tools consist of networks of opaque complex algorithms making them increasingly difficult to understand. Although these phenomena of algorithm aversion and algorithm appreciation are observed, the individual and situational characteristics that may lead to such varied results are still unclear. Further research is needed to address the question of who is more likely to respond with "aversion" or "appreciation" when presented with the opportunity to adopt AI.

The variance in people's willingness to adopt AI may be better understood by examining individual differences in personality traits and self-concept of their abilities. While personality traits have been identified as important for predicting technology adoption be-

havior (e.g., Park & Woo, 2022), the mechanisms occurring between personality trait expression and actual adoption behavior are unclear. The extensive work in the information systems literature on technology acceptance models provides a theoretical foundation for understanding this gap. Broadly, technology acceptance models indicate that the influence of external variables (i.e., environment, technology, and individual characteristics) on adoption behavior is mediated by one's perceptions about the technology's ease of use, usefulness, and other key belief variables. The Technology Acceptance Model (TAM) (F. Davis, 1986; F. D. Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), as well as their iterations, are the most often used models for predicting technology adoption via user perceptions about a technology. TAM and UTAUT have been applied to a variety of specific use contexts (Schepers & Wetzels, 2007) but their applications to AI technology are wanting. Park and Woo (2022) recently observed that while many studies incorporate technology contexts that may use AI, that aspect is not made explicit in the studies.

Matthews and colleagues (2021) have expressed that personality research, particularly relevant trait models, plays a role in understanding the human-centered challenges of adapting to new contexts of human-automation interaction. Additionally, Venkatesh (2022) recently offered a research agenda theoretically grounded in the UTAUT model by suggesting that researchers explore how other variables such as individual and environmental characteristics influence AI adoption behaviors. Furthermore, results from a recent meta-analysis conducted by Seibert and colleagues (2021) indicated that only 22 articles in the prior 14 years had been published examining personality's influence on technology acceptance models – none of which focused on AI. Researchers seem to be approaching the AI adoption problem primarily by examining technology design (e.g., Santamaria & Nathan-Roberts, 2017), dynamic interaction processes such as trust calibration (e.g., Zhang & Dafoe, 2019) or theory of mind (e.g., Cuzzolin et al., 2020), rather than more stable human characteristics such as personality traits or self-concept.

When it comes to understanding the impact of self-perceptions on technology adoption, studies tend to lean toward self-efficacy; a similar but conceptually different construct that concerns whether someone perceives themselves as able to successfully use the technology in question (e.g., Liu et al., 2022) or computers in general (e.g., Chiu & Wang, 2008). However, as AI continues to be developed to aid in various ability domains, it is important to take an interactionist perspective to understand how both individual differences and use context relate to broader technology adoption.

1.2 Purpose

This study aimed to understand whether personality traits influence beliefs about and intentions toward adopting AI to augment decision-making in various contexts. Venkatesh and colleagues' (2003) UTAUT provides a robust framework for taking an individual-differences approach to understanding adoption behaviors. Both the reported mixed attitudes people hold towards AI, and the lack of research empirically examining how personality traits impact pre-adoption attitudes toward AI led to the following broad research question:

RQ1: How much do personality traits and self-concept of domain ability influence people's intentions to adopt AI for decision-making independently and via the UTAUT model?

Furthermore, current research in this area is limited by an abundance of studies examining specific technologies and use contexts leading to poor generalizability (e.g., Siebert et al., 2021). With AI being applied to many contexts, it was important to take broader situational factors into account. For example, an individual may be more willing to adopt an AI to assist them with a task in a domain which they perceive they have a deficit in hopes that the tool may compensate for this. Conversely, those who perceive themselves as having high ability in a domain may question the value an AI would add to what they already perceive themselves as competent at. This approach aimed to address a gap in technology acceptance modeling research that has primarily been based on context-specific technolo-

gies rather than considering technology across various use cases, and led to the following research question:

RQ2: How willing are people to adopt AI assistance in contexts for which they perceive they have a high (or low) ability?

CHAPTER 2

LITERATURE REVIEW

The following chapter discusses the relevant literature and theoretical foundations that provided the basis of this study. First, I will define AI, focusing on the technologies that are used to aid decision-making, and highlight the characteristics of AI that may have led to mixed attitudes. Next, I will explain the trait-based approach to personality, focusing on the models and traits of interest to the study. Then, I will review self-concept of ability and describe its influence on behavior. Next, I will explain the theoretical framework of technology acceptance models, and previous research incorporating personality and self-concept traits. I will then describe the conducted study, detailing the proposed hypotheses. The methodologies of this proposed study will be detailed in Chapter 3 and the results of hypothesized and exploratory analyses in Chapter 4. Finally, Chapter 5 will conclude with interpretations of the results, implications, and future directions.

2.1 Artificial Intelligence

When reviewing AI literature, it becomes apparent that AI has been conceptualized in a variety of ways, likely due to it being influenced by so many fields with various goals (Russell & Norvig, 2021). Returning to the conception of AI's definition from the Dartmouth Research Project in 1955, the researchers involved defined it as the problem "... of making a machine behave in ways that would be called intelligent if a human were so behaving." (McCarthy et al., 1955, p. 11). This trend of using human intellectual capabilities such as learning, problem-solving, and decision-making as a comparison for artificial intelligence has persisted as a popular conceptualization (Kaplan & Haenlein, 2019; Park & Woo, 2022). However, AI has also been defined as a broad field of study as well as a theoretical framework (Chen et al., 2020). Most scholars would likely agree that AI refers

to machines that can autonomously process various types of information and act rationally based on that information (Russell & Norvig, 2021).

AI can be embodied in a variety of forms that range from more physical (e.g., robotics) to deeply embedded in software systems (e.g., social media content management) depending on their intended use (Glikson & Woolley, 2020). According to Russell and Norvig (2021), these various embodiments could all be classified as “intelligent agents” that perceive and process information from the physical or digital environment to perform actions. While AI in pop culture and media is often depicted as being capable of handling many problems, most intelligent agents are only capable of performing narrow or specific tasks with the use of complex algorithms (IBM Cloud Education, 2020). My study focused on a particular use case of embedded artificial intelligence for aiding decisions made in various contexts. The following section will describe various types of decision aids in more detail, but for brevity, the term AI from here on will be used as an umbrella term while recognizing that some tools colloquially referred to as AI may not be specifically classified as such.

2.1.1 AI and Decision-Making

Intelligent decision-support machines emerged in the late 1960s and early 1970s and were used in practical applications of decision-making around the early 1980s (Watson & Mann, 1988). Such technologies have only continued to develop and are referred to by a variety of names in the literature such as intelligent decision support systems, expert systems, recommender systems, information retrieval systems, suggestion models, etc. (Aggarwal, 2016). While many are functionally and contextually distinguished, all are intended to improve the human decision-making process by executing decisions autonomously or by presenting people with information or suggestions to support decision-making (Aggarwal, 2016). The literature examining the use of AI for decision support often regards two broad interaction contexts: decision automation and decision augmentation. Decision automation describes a situation in which a decision is made and executed by an AI without human

control (Langer & Landers, 2021). Decision augmentation refers to situations in which technology is leveraged in providing information to human decision-makers to improve decision efficiency and accuracy (Langer & Landers, 2021).

Some researchers further classify decision automation and augmentation by using Parasuraman and colleagues' (2000) ten levels of automation which describes the ratio between human control and AI autonomy in a decision context. On this proposed spectrum, a "1" is associated with a context where the computer offers no assistance and the human executes all decisions and actions, and a "10" is described as a context in which the computer decides everything and acts autonomously, ignoring the human. My study dealt with AI that augments the decision-making process. This situation is best defined by Parasuraman's 5th level of automation in which the system provides a suggestion to the user and will execute the action if the user approves of it (Parasuraman et al., 2000). However, despite the utility that this decision-supporting technology offers in numerous situations, AI is not without its issues and limitations.

2.1.2 Problematic Characteristics of AI

There are a few problematic characteristics of most AI technologies that are key to influencing how people think about them. First, AI suffers from the "black box" problem which occurs when a system's underlying processes beyond inputs and outputs are opaque from human understanding (Rudin & Radin, 2019). This opacity is most problematic with those AI that use unsupervised and deep learning strategies which result in poor interpretability even among experienced computer scientists and engineers (von Eschenbach, 2021). Even simpler algorithms require a level of individual knowledge to understand their underlying functionality. The black-box nature of AI is a problem for a few reasons. This lack of transparency is often cited as a leading factor contributing to people's hesitance toward adopting AI (e.g., Schmidt et al., 2020; von Eschenbach, 2021). Lack of system transparency and poor interpretability may influence users to distrust or mistrust the system's capabilities

leading to potential errors in use (Lee & See, 2004). While this issue of transparency and lack of user understanding is not new in the realm of human-machine interaction, the black box problem in AI further complicates the broader issue of interpretability and adoption.

Furthermore, AI, like other model-based technologies, is prone to error due to factors such as poor datasets and initial coding errors. The models that underlie these technologies can also reflect unintended biases that are either pre-programmed by humans or emerge through unsupervised machine-learning processes (Smith, 2018). One such occurrence is popularly referenced with Amazon's AI employee screening system, AMZN.O, which disproportionately favored recommending male applicants for hire over female applicants (Dastin, 2018). Issues of model bias, errors, and malfunctioning are further exacerbated by the black box problem, making it increasingly difficult for computer engineers to identify and resolve any underlying problems. Given the opacity of these systems, human-centered researchers are examining the cognitive processes that occur in human-AI interactions. Venkatesh (2022) proposed individual differences in personality as a potential explanation for understanding who is willing to use AI despite these problematic characteristics.

2.2 Personality

Personality has been well-established as a core factor in understanding humans on a variety of levels including predicting attitudes, (Ajzen, 1998), emotions (Reisenzein et al., 2020), intellectual development (Ackerman, 1996; Ackerman & Heggestad, 1997), work performance (Barrick & Mount, 1991) and so on. While there have been various conceptualizations of personality, one of the most prevailing approaches to understanding personality is the trait-based approach (Allport, 1937; John & Srivastava, 1999). According to the trait approach to personality, individuals' affective aspects can be described in terms of a large, but finite number of personality characteristics or traits (Ajzen, 2005). Personality traits are conceptualized as relatively stable characteristics that describe the tendencies of an individual and how these tendencies differ from others (Tett & Guterman, 2000). The 3,320

personality trait-relevant items listed on the open-sourced International Personality Item Pool (IPIP) (Goldberg et al., 2006) are a testament to the extensiveness of this approach.

In the present study, personality was introduced as a variable of interest for two main reasons. The first is that there is a general lack of research regarding the influence of personality traits on attitudes toward technology and adoption behaviors. Among these studies, most are limited in their generalizability due to focusing on attitudes and adoption of specific technologies (e.g., Barnett et al., 2015; Devaraj et al., 2008; Svendsen et al., 2013). The second reason is that while AI continues to be embedded and used in more task domains, it becomes increasingly important to examine variables that may predict adoption behavior across various use cases. Personality traits are valuable in taking a person-centric individual difference approach to understanding people's varied responses to AI.

2.2.1 Five-Factor Model

The Five-Factor Model (FFM) of personality (i.e., The Big Five) is one of the most used personality assessments in research that represents personality at its broadest level (Goldberg, 1981). The FFM does not imply that personality is reduced to only five traits, rather, the model indicates that people tend to differ on five broad dimensions: openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism (reverse coded as emotional stability) with each broad factor relating to various facets of more specific traits (Digman, 1990). The FFM is often criticized for its lack of theoretical foundation, due to its factors being established statistically on the shoulders of lexical approaches to personality (John & Srivastava, 1999). However, its wide use and predictive contributions to various empirical research are vast (e.g., personnel selection) (Barrick & Mount, 1991). This popularity is also reflected in the technology acceptance literature with one or more of its core traits almost exclusively representing the personality extensions to technology acceptance models (Siebert et al., 2021).

2.2.2 Tellegen's Model

Tellegen's (1982) model of personality, assessed with the Multidimensional Personality Questionnaire (MPQ), proposes eleven personality dimensions that load on three higher-order traits when factor analyzed. These three higher-order traits are (1) positive affectivity, (2) negative affectivity, and (3) constraint. The positive affectivity factor is associated with three traits, well-being, social potency, and achievement. Negative affectivity is associated with the three traits of stress reaction, alienation, and aggression. Lastly, constraint includes the three traits of control, harm avoidance, and traditionalism (Tellegen, 1982).

Two of Tellegen's (1982) lower-order traits, social potency ($r = .47$) and social closeness ($r = .51$) were used in this study to capture two major sub-facets of extraversion. Individuals who score high in social potency are characterized as those who enjoy leadership roles, are forceful and decisive, take charge, and like to influence others and be noticed at social events (Tellegen, 1982). Individuals who score high in social closeness are characterized as sociable, warm, and affectionate. They tend to like people, take pleasure from and value close personal ties, and turn to others for comfort and help (Tellegen, 1982)(Tellegen, 1982). Furthermore, social potency and social closeness are correlated with sub-facets of the FFM's extraversion as measured by NEO (Church, 1994). Social potency correlated most highly with assertiveness ($r = .67$) and activity ($r = .31$), while social closeness correlated most highly with warmth ($r = .53$), gregariousness ($r = .56$), and positive emotions ($r = .43$) (Church, 1994).

2.3 Self-Concept of Ability

Self-concept has been broadly defined as, "a person's perception of [one]self," and is described as, "...organized, multifaceted, hierarchical, stable, developmental, evaluative, [and] differentiable." (Shavelson et al., 1976). These perceptions tend to be formed particularly through information reinforced by the environment and self-comparisons to relevant

others (Shavelson et al., 1976). When defining self-concept, it is also necessary to distinguish the construct from others that may be incorrectly used synonymously such as self-efficacy and self-esteem. Most simply, these three constructs can be differentiated in terms of their breadth of self-evaluation. Self-esteem has to do with broad, global perceptions about the self (Rosenberg, 1965), self-concept relates to domain-specific perceptions of the self (Shavelson et al., 1976), and self-efficacy concerns task-specific perceptions of ability (Bandura, 1977). Marsh (2006), in collaboration with Shavelson (e.g., Marsh & Shavelson, 1985; Marsh et al., 1988), created a theoretical model indicating that self-concepts are established at the domain level (i.e., academic, social, emotional, and physical). The abilities of interest to this study were those that fell in the academic category (i.e., math, verbal, spatial). These constructs are measured by having people read a series of statements and indicating the extent to which they think the statement reflects their skills and abilities. In this study, I also examined an additional ability domain, organizational ability, as relevant to the AI assistant context. In this case, organizational self-concept was defined as the perceptions of one's ability to both establish and keep order among various aspects of life such as tasks, objects, and concepts. Details of the creation of measure items for this construct can be found in the methodology section. The reliability and validity of self-estimates have been examined with objective tests (e.g., Ackerman & Wolman, 2007; Freund & Kasten, 2012), and various correlations with self-concept have been examined including age, gender, academic achievement, and socio-economic status (Marsh, 1990). Like personality traits, one's ability self-concept may inform technology adoption behavior. With the application of AI tools in various domains, one's intention to adopt an AI tool may be a function of their ability self-concept for the domain it is being applied to. Furthermore, the addition of academic self-concept variables was intended to better understand the situational aspects of AI tool adoption. If such tools are created to assist individuals in particular domains, one's self-concept of their abilities in that domain may determine whether they perceive a tool as making up for a deficit in ability or unnecessary.

2.4 Propensity to Trust

Trust in automation has become a popular topic, particularly among human factors and engineering psychologists (Glikson & Woolley, 2020) to address problems associated with the black-box nature of AI. The opacity of automated technology including AI results in a situation that calls for people to trust the device. Currently, the most recognized and used definition of trust in automation is, "...the attitude that an agent will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability." (Lee & See, 2004, p. 54). For an individual to establish an evaluation of trust in something, they must first recognize and accept that risk is involved in doing so. This aspect is what differentiates trust from other variables such as confidence or predictability (Mayer et al., 1995). In an AI adoption situation, perceptions of risk are likely to stem from the indeterminant outcomes associated with relying on AI as well as the situational consequences were the system to err. Hoff and Bashir (2015) have synthesized the literature on trust and proposed a three-layer model describing the sources of variability in human-automation trust: dispositional, situational, and learned trust.

Propensity to trust (also referred to as dispositional trust) is conceived as a relatively stable trait that indicates one's general willingness to trust others (Hoff & Bashir, 2015; Mayer et al., 1995). Differences in people's trust propensities are proposed to be attributed to differences in developmental experiences, cultural background, and hereditary factors (e.g., Loehlin, 1992). This general willingness to trust others has been proposed as most likely to influence one's overall perceptions of trustworthiness when relevant information about the trustee is vague and uncertain (Mayer et al., 1995; Rotter, 1971). These situational characteristics are reflected in the decision of whether to adopt an AI as an aid to decision-making due to the opacity that is common among such tools. In such cases where AI provides diagnostic information related to its functioning, this information can be limited and reliant on the user's ability to interpret it in a meaningful way.

2.5 Technology Acceptance Models

Technology acceptance models are founded on a theoretical framework that combines the Theory of Reasoned Action (TRA) and the Theory of Planned Behavior (TPB) which propose the links between beliefs and intentions to perform a behavior with actual behavior (see reviews: King & He, 2006; Marangunić & Granić, 2015). Davis (1989) synthesized these theories to better understand the acceptance or rejection of new technologies in the workplace and proposed that user adoption is based on three primary constructs, perceived usefulness (PU), perceived ease of use (PEOU), and behavioral intention to use (BI) the system. Perceived usefulness is the degree to which an individual believes that using a technology will improve their performance or fulfill an advantageous purpose if used. Perceived ease of use refers to the degree to which an individual believes that using a technology will be free of effort. It should be noted that Davis' (1989) conceptualization follows the definition of ease being, "freedom from difficulty or great effort," and it is implied that intentional technology use will involve some expense of one's allocated effort. Lastly, behavioral intention to use a technology consists of a user's overall evaluation of whether they would intend to use the technology in question to improve their performance. While the original conceptualization of TAM was intended to predict information system (IS) technology adoption in the workplace (F. D. Davis, 1989), it has since been applied to a myriad of other technologies and adoption contexts such as internet use, e-commerce, online gaming, telemedicine, and electronic mail to name a few (Schepers & Wetzels, 2007; V. Venkatesh & Davis, 2000)).

2.5.1 Unified Theory of Acceptance and Use of Technology (UTAUT)

One prominent extension to TAM is the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003). Venkatesh and colleagues (2003) sought to combine several theoretical models into one unified model for predicting technology ac-

ceptance and use behavior. This resulted in the creation of UTAUT, a theory that integrates eight other extant theories and models: the Theory of Reasoned Action (TRA), the Technology Acceptance Model (TAM), the Motivational Model, the Theory of Planned Behavior (TPB), a combined TBP/TAM model, the Model of PC Utilization, Innovation Diffusion Theory (IDT), and Social Cognitive Theory (SCT). Venkatesh and colleagues' (2003) seminal article found that their proposed UTAUT model predicted more of the variance in individuals' intentions to use technology ($R^2_{adj.} = .69$) compared to the other eight models ($R^2 = .17 - .53$).

UTAUT proposes four variables that directly influence one's intention to use a particular system or technology: performance expectancy, effort expectancy, social influence, and facilitating conditions. The unified theory also introduced individual differences and situational variables as moderators including gender, age, experience level with the technology, and the degree to which the use of the technology is voluntary. The first key variable, performance expectancy, is defined as the degree to which an individual perceives a technology as being beneficial to helping improve their job performance. Like TAM's perceived usefulness, this is UTAUT's strongest predictor of behavioral intention to use a technology. Performance expectancy is moderated by gender and age. Effort expectancy is defined as the degree of ease that is associated with the use of a system or technology. If individuals perceive a new technology as requiring more effort to use, their behavioral intentions to use the technology are lowered. UTAUT proposes that effort expectancy is moderated by gender, age, and the user's level of experience with the technology.

Social influence refers to the degree to which an individual perceives that their use of a technology is important to relevant others. Broadly, this encompasses the notion that people's behavior is influenced implicitly or explicitly by how they are or may be viewed by others. Individuals who perceive their use of a technology to be important to relevant others will have higher behavioral intentions to do so. Social influence is moderated by gender, age, experience, and how voluntary the use of the technology is. Lastly, facilitating

conditions relate to whether an individual perceives there to be adequate resources and support for using a technology by some entity. This variable has a direct effect on actual system use rather than an indirect one through behavioral intention (Venkatesh et al., 2003). Facilitating conditions were omitted from the model in the current study because the scope of this study concerned understanding people's attitudes toward using AI in a broad range of task contexts rather than the impact that external entities have on adoption intentions. As such, the contexts examined in this study might have various facilitating entities, so perfect facilitating conditions were assumed to reduce noise in the data between contexts.

2.5.2 Personality, Self-Concept, and Technology Acceptance

Several studies have explored personality trait relationships with the TAM constructs via the FFM. Devaraj and colleagues (2008) tested how the FFM personality traits influenced the use of a collaborative information system technology among a sample of 180 students. Their structural equation model indicated that conscientiousness moderates the relationship between perceived usefulness and intentions as well as subjective norms and intentions by strengthening them. They found that extraversion moderates the relationship between subjective norms (i.e., social influence) and behavioral intentions such that their relationship is strengthened. They also found a negative relationship between neuroticism and perceived usefulness and a positive relationship between openness and perceived usefulness. Lastly, they found that agreeableness is positively related to perceived usefulness and that it moderates the relationship between subjective norms and intentions.

Svendsen and colleagues (2013) also examined the FFM traits and their relation to using a digital media storage system among a sample of 1,004 Norwegian adults with an average age of 45. Svendsen and colleagues found that the effect of extraversion on behavioral intentions ($r = .11$) was fully mediated by perceived usefulness ($r = .20$) and perceived ease of use ($r = .21$). They hypothesized that the effect of conscientiousness on behavioral intentions ($r = .23$) would be significant when individuals were interested in the technol-

ogy domain and found support for this hypothesis, however, the effect was fully mediated by perceived usefulness ($r = .21$) and perceived ease of use ($r = .27$). Conscientiousness without the interest variable had small correlations with behavioral intentions, ($r = -.03$), perceived usefulness ($r = -.03$) and perceived ease of use ($r = .01$). Emotional stability was found to have a direct positive relationship with behavioral intention ($r = .06$), and perceived ease of use ($r = .09$) and openness to experience had a positive relationship with perceived ease of use ($r = .18$) but not behavioral intention ($r = .05$).

While most studies have focused on personality relationships with the TAM model, several have also incorporated the FFM traits into the UTAUT model. Barnett and colleagues (2015) examined a sample of 382 college students and assessed how the FFM traits influenced their adoption of an online course management system. They found a direct effect of conscientiousness on actual system use ($r = .17$) and perceived system use ($r = .14$) unmediated by behavioral intention to use ($r = .15$). Openness was not found to have any significant relationship with actual use ($r = -.05$), perceived use ($r = -.10$), or intentions to use ($r = .06$). Neuroticism was found to have a significant negative relationship with actual system use ($r = -.18$) and perceived system use ($r = -.09$) unmediated by behavioral intention ($r = -.07$). Unexpectedly, they found extraversion to have a significant negative relationship with actual system use ($r = -.21$) but no significant relationships with perceived system use ($r = -.03$) or behavioral intentions ($r = -.02$). Finally, agreeableness was significantly related to behavioral intentions ($r = .29$) but not perceived system use ($r = .10$) or actual system use ($r = .11$).

A recent meta-analysis by Siebert and colleagues (2021) found 22 studies that examined the tested relationships of personality traits on TAM constructs. They found that studies primarily incorporate the FFM traits, openness to experience, extraversion, agreeableness, conscientiousness, and neuroticism and four studies looked at willingness to take risks. Consistent with the present literature review, they found that technology contexts were widely varied and thematically divided them into four domains: project management

and organization, social network sites and messaging, commerce, government, security, and others (i.e., autonomous driving and smartphones).

As for ability self-concept, no research studies emerged in the literature review that examined academic self-concept with the technology acceptance models. However, a related construct, self-efficacy, has been well-researched in the context of technology acceptance (Chiu & Wang, 2008; Liu et al., 2022; V. Venkatesh & Davis, 1996). In these cases, self-efficacy tends to be conceptualized as general computer self-efficacy or self-efficacy for related technology use behaviors. Self-efficacy and self-concept have been argued to be related such that self-efficacy judgments contribute to the formation of broader self-concept judgments in domains (Bong, 1999; Schunk, 1991). With no uncovered empirical evidence relating self-concept to technology adoption, this study relied on empirical support from self-efficacy studies to inform the hypothesized predictions. While it has been reasonable to pursue self-efficacy as a specific influential variable predicting technology adoption, it may be too narrow a construct when considering a broad domain range of AI applications. As such, the current study incorporated ability self-concept to examine how perceptions of one's ability in a domain influenced their adoption of AI that seeks to assist them in relevant domains.

2.6 The Present Study

I used the UTAUT model as a foundation for understanding how key personality traits and ability self-concept influence willingness to use AI to aid decision-making. It sought to address a critical point in technology adoption – that is the initial cognitive processes in which someone determines whether to use AI. While previous research has indicated relationships between personality and technology adoption, this study examined the mechanisms explaining this relationship by also focusing on the situational aspects that may be better understood by individual differences in personality and self-concepts of abilities.

2.6.1 Hypotheses

The following section outlines the hypotheses of the presented study, as well as the key rationale behind them. The effect sizes for the proposed hypotheses were interpreted using Cohen's (1988) f^2 criteria in terms of proportion of variance (R^2) with .02 considered small, .15 considered medium, and .35 considered large effects.

Extraversion (Social Potency Social Closeness)

Extraversion characterizes individuals who tend to be more social, outgoing, and seek stimulation through activities and interpersonal relationships (Digman, 1990). As it pertains to the workplace, those higher in extraversion are more likely to succeed and show high performance in management and sales positions (Barrick & Mount, 1991). Additionally, extraversion often contributes to effectiveness in team settings (Barrick et al., 2001). Concerning technology, Svendsen and colleagues (2013) observed a small correlation between extraversion and intentions to use a software tool designed to store digital contents such as images, music, and other files ($r = .11$). Another study by Devaraj and colleagues (2008) also found a small correlation between extraversion and behavioral intentions to use a collaborative work system ($r = .12$). Overall, studies tend to report positive correlations between extraversion and behavioral intentions to use various forms of technology (e.g., Devaraj et al., 2008; Svendsen et al., 2013; V. Venkatesh et al., 2014). Other studies only tested the effects of personality on UTAUT's mediating variables rather than behavioral intentions directly (e.g., Boontarig, 2016; Özbek et al., 2014). Higher scorers may prefer to facilitate their interpersonal interactions while lower scorers (i.e., introverts) may find personal benefit and preference allowing an AI to facilitate interpersonal interactions for them. I also considered two major facets of extraversion, social potency, and social closeness (Tellegen, 1982). Those high in social potency are described as being forceful and decisive with low scorers tending to prefer that others take charge and make decisions. Furthermore, individuals high in social closeness are sociable and value close interpersonal

ties while low scorers prefer to be alone and work problems out without others.

Neuroticism

Neuroticism (often reverse-coded as emotional stability) is the degree to which people experience higher negative emotionality, are less emotionally stable, and tend to experience anxiety more often (Digman, 1990). Svendsen (2013) found that emotional stability did have a small correlation with behavioral intentions ($r = .06$), and Devaraj et al. (2008) found a small negative correlation between neuroticism and behavioral intentions ($r = -.17$). The opaque nature of AI technologies may exacerbate feelings of anxiety for those high in neuroticism leading to poor expectations of system performance and higher perceptions of effort in using the device. On the other hand, AI may also offer a means of relieving negative feelings that people high in neuroticism may often face such as using an AI tool to assist with difficult decision-making by suggesting optimal choices.

Propensity to Trust

Propensity to trust is described as a relatively stable personality trait that indicates someone's general willingness to trust others and is most predictive in situations where information about the trustee is vague and uncertain (Hoff & Bashir, 2015; Mayer et al., 1995). Previous research incorporating trust in technology acceptance models often focused on perceptions of trustworthiness rather than the effects of dispositional trust on the TAM or UTAUT beliefs (Wu et al., 2011). However, Wu et al.'s (2011) meta-analysis supports the important role of trust in the TAM with trust being correlated with perceived usefulness ($r = .51$), perceived ease of use ($r = .47$), and behavioral intentions to use technology ($r = .48$). Propensity to trust has also been found to be related to the FFM traits of agreeableness, neuroticism, and openness (Alarcon et al., 2018). Trusting involves evaluating the potential benefits and costs of deciding to trust another entity indicating that those high in propensity to trust are more likely to maximize beliefs associated with benefits such as per-

formance expectancy and minimize beliefs associated with costs such as effort expectancy (Alarcon et al., 2018). Furthermore, those high in propensity to trust are more likely to tend to trust the judgments of those in their relevant social circle indicating a potential positive relationship with social influence.

Overall, the personality traits of extraversion and neuroticism seem to have the most consistent empirical support as important for predicting behavioral intentions in various contexts compared to the other FFM traits, openness, agreeableness, and conscientiousness. Additionally, propensity to trust, a less explored personality trait in this context, was hypothesized to be generally important to the specific technology context of AI. This led to the following overarching hypothesis related to the impact of personality in predicting behavioral intentions.

H1: Personality traits in the aggregate will account for 8 percent of the variance in behavioral intentions independently and will account for 5 percent of the variance over and above the UTAUT core constructs when entered into a hierarchical regression.

Self-Concept of Abilities

Academic self-concept refers to individuals' knowledge and perceptions about themselves in achievement situations (Bong & Skaalvik, 2002) with this study having focused on the domains of math, verbal, spatial, and organizational abilities. While the present literature search did not reveal an application of specific ability self-concepts with technology acceptance models, research has been conducted linking self-efficacy to behavioral intentions to use various technologies (e.g., Chiu & Wang, 2008; Liu et al., 2022; V. Venkatesh & Davis, 1996). Research on self-efficacy and technology adoption were used to inform predictions of the relationships of self-concept. Computer self-efficacy correlated with continued usage of web-based learning ($r = .47$) (Chiu & Wang, 2008), as well as behavioral intentions to use AI-based healthcare systems ($r = .42$) (Kwak et al., 2022), and mobile health services ($r = .62$) (Liu et al., 2022). Mobile device self-efficacy was found to correlate with be-

havioral intentions to engage in mobile learning ($r = .40$) (Chao, 2019). Self-efficacy for using technologies was found to be correlated with behavioral intentions to use or continue to use those technologies ($r = .40 - .62$) in the retrieved studies. Academic self-concept was expected to have a somewhat small effect on behavioral intentions to use AI in general when compared to self-efficacy perceptions are directly related to the task of using the technology.

H2: Self-concept of academic abilities in the aggregate will account for 10 percent of the variance in behavioral intentions independently and will account for 8 percent of the variance over and above the UTAUT core constructs when entered into a hierarchical regression.

Previous studies from the algorithm aversion/appreciation literature have examined the impact of self-report domain expertise on the willingness to take advice from statistical algorithms (e.g., Logg et al., 2019). Results from such studies tend to indicate that those with expertise (actual or perceived) are more likely to view a tool intended to aid in their domain of expertise to be unnecessary. Similar patterns have emerged in personnel selection literature seeking to understand why HR professionals might over-rely on intuitive judgment rather than statistical selection procedures (Highhouse, 2008). In contrast to high self-evaluations of ability, it may be that people are more likely to use assistive AI technology for domains in which they have a low self-concept, viewing it as a means to compensate for a perceived self-deficit in domain ability. This led to the following hypothesis related to ability self-concept and behavioral intentions to use an assistive AI.

H3: Personality (extraversion and neuroticism) and self-concept of ability variables (math, verbal, spatial, and organizational ability) will independently account for 13-15 percent of the variance in behavioral intentions to use AI and 10-13 percent of the variance over and above the UTAUT core constructs when the variable corresponds with the use domain.

CHAPTER 3

METHOD

3.1 Participants

Participants for this study were recruited from Prolific, an online research participant recruitment and management platform. Participation in this study required participants to be a student or employed (full- or part-time), at least 18 years of age, and fluent in comprehending the English language. This sample was chosen over an undergraduate university sample to diversify the age range and gain a more representative sample of working adults. Upon completion of the study participants were compensated \$8 for their time. An a priori power analysis was conducted using G*Power3 (Faul et al., 2007) to determine the required sample size to test the hypothesis with the smallest effect. The results indicated that this study would require a minimum of 223 participants to achieve 80% power for detecting the smallest estimated effect (.05) at a significance criterion of $\alpha = .05$. Data from 241 participants were collected, 231 of which were included in the analyses.

Because all participants were recruited via Prolific, several measures were put in place to screen for poor data quality and inform data exclusions. Participants responded to a commitment and effort check at the beginning and end of the survey respectively (Appendix H) per guidelines provided in Abbey and Meloy's 2017 publication. These questions also required participants to type their responses, potentially assisting with bot screening. Responding "No" to either of these statements resulted in exclusion from analysis. Two participants were excluded for their responses to the concluding effort statement. This study also employed the IP threat score methodology described in Bernerth and colleagues' 2021 publication on detecting false identities and improving online data validity. IP threat scores were determined with the following open-access analytic tool found at

<https://getipintel.net/>. Other data quality metrics included survey completion time, reverse-scored measure responses, and overall response patterns. None of the participants had completion times at least 2 standard deviations below the mean, however, six participants completed the study quickly (about one standard deviation below the mean) and were identified as having little to no variation in their response patterns. Two participants failed the IP address score check, completion time, and response variance in combination resulting in a total of ten participant exclusions.

The final sample consisted of 126 (54.55%) females and 105 (45.45%) males. Responses to gender identification matched legal birth sex except for one individual who reported their gender as non-binary. The average age of the sample was 39.44 ($SD = 11.89$, $Min = 18$, $Max = 74$). As for employment status, the sample had 195 (84.42%) strictly working adults and 36 (15.58%) students who reported also working full- or part-time. Among the strictly working adults, 150 (76.92%) were employed full-time and 45 (23.08%) were employed part-time. Among the students, 22 (61.11%) were also employed full-time, and 14 (38.89%) were employed part-time. As for highest levels of education, 90 participants reported having a bachelor's degree, 39 had a high school diploma, 31 had an associate's degree, 27 had some college, 25 had a master's degree, 4 completed technical school, 3 doctoral degrees, 1 attended some high school, 1 attended some technical school, and 10 participant's education was unknown. Participant sample demographics can be found in Table 3.1.

3.2 Materials and Measures

3.2.1 UTAUT Construct Measures

Acceptance of AI was measured with the Unified Theory of Acceptance and Use of Technology model (Venkatesh et al., 2003, 2012) (Appendix A). Measures for the core UTAUT constructs were adapted from the more consumer-focused UTAUT2 (Venkatesh et al., 2012). Internal consistency reliability (Cronbach's α) for these items were as follows: per-

Table 3.1: Descriptive Statistics for Demographic Variables

Demographic	N	%
Sex	-	-
Male	105	45.45%
Female	126	54.55%
Gender	-	-
Man (including Trans Male/Trans Man)	104	45.02%
Woman (including Trans Female/Trans Woman)	126	54.55%
Non-Binary	1	0.43%
Education	-	-
Some High School	1	0.43%
High School Diploma	39	16.88%
Some Technical School	1	0.43%
Technical School	4	1.73%
Some College	27	11.69%
Associate's Degree	31	13.42%
Bachelor's Degree	90	38.96%
Master's Degree	25	10.82%
Doctorate Degree	3	1.30%
Education Unknown	10	4.33%
Employment Status	-	-
Employed Full-Time	150	64.93%
Employed Part-Time	45	19.48%
Student	36	15.58%

Note. Total sample $N = 231$. Sample age $M = 39.44$, $SD = 11.89$.

formance expectancy ($\alpha = .88$), effort expectancy ($\alpha = .91$), social influence ($\alpha = .82$), and behavioral intention ($\alpha = .93$) (Venkatesh et al., 2012). While usually measured on a 1 to 7 Likert-type scale, this study employed an even-numbered scale of 1 (“Strongly disagree”) to 6 (“Strongly agree”). Each of the UTAUT constructs were anchored on this 6-point scale. Furthermore, the prompts for each questionnaire were appropriately worded to coincide with the AI decision support technology context (e.g., “Using [mobile internet] helps me accomplish things more quickly,” was modified to, “Using this AI would help me accomplish things more quickly.”). Effort expectancy was measured with four items, while performance expectancy, social influence, and behavioral intentions were each measured with three items for a total of 13 items.

3.2.2 Five-Factor Model Personality Measures

Extraversion and neuroticism personality traits were measured using items from the International Personality Item Pool (IPIP) collection (Goldberg, 1999; Goldberg et al., 2006) (Appendix B). Internal consistency reliability (Cronbach's α) are as follows: extraversion ($\alpha = .91$), and neuroticism ($\alpha = .91$). These items have been found to correlate positively with the NEO-PI-R (Costa & McCrae, 2008) measure of extraversion ($r = .79$) and neuroticism ($r = .86$). Both traits were measured with 20 items, 10 of which are reverse scored. Item responses were measured on a 6-point Likert scale anchored by how accurate the statement is in describing the participants ranging from 1 ("Very inaccurate") to 6 ("Very accurate").

3.2.3 Tellegen's Model of Personality Measures

The two facets of extraversion, social potency, and social closeness were measured with items from Tellegen's Multidimensional Personality Questionnaire (MPQ) (Tellegen, 1982) (Appendix C). While the original response options of this measure were binary ("True" or "False"), for this study the response anchors were modified to a 6-point Likert-type scale ranging from 1 ("Very inaccurate") to 6 ("Very accurate"). Internal consistency reliability (Cronbach's α) for the constructs are as follows: social potency ($\alpha = .87 - .89$) and social closeness ($\alpha = .85$). The measure showed high stability over a thirty-day test-retest interval (social potency $\alpha = .82$; social closeness $\alpha = .92$) (Tellegen, 1982). Social potency was measured with 26 items and social closeness was measured with 22 items.

3.2.4 Propensity to Trust

Propensity to trust was measured with a four-item questionnaire that asks about individuals' trusting tendencies on a 6-point Likert scale ranging from 1 ("Strongly disagree") to 6 ("Strongly agree") (Appendix D). While usually measured on a 1 to 7 Likert-type scale, this study employed an even numbered scale. Internal consistency reliability (Cronbach's α) for

the trust propensity measure was $\alpha = .88 - .89$. Fraizer and colleagues (2013) conducted two validation studies testing convergent and discriminant validity of their propensity to trust measure. The results of these studies indicated that propensity to trust was related, but conceptually distinct, from similar constructs including trust ($r = .16 - .28$), optimism ($r = .27$), and perceptions of trustworthiness facets; ability ($r = .07 - .24$), benevolence ($r = .14 - .27$), and integrity ($r = .13 - .24$).

3.2.5 Self-Concept of Abilities

Self-concept of academic abilities (i.e., math, verbal, and spatial) was measured with a version of Goff's (1994) self-concept measure that has been revised and validated by Ackerman, Kanfer, and colleagues (e.g., Ackerman et al., 2001) (Appendix E). Ability self-concept was measured by having participants read a series of statements and indicating the extent to which they think the statement reflects their skills and abilities on a 6-point Likert-type scale ranging from 1 ("Strongly disagree") to 6 ("Strongly agree"). This measure consisted of 17 items with internal consistency reliabilities as follows: verbal ($\alpha = .85$), math ($\alpha = .82$), and spatial ($\alpha = .78$). Questions for an additional self-concept domain, organizational ability, were created for this study using the pre-established domain items as guidance. The organizational ability self-concept variable consisted of 8 items ($\alpha = .88$).

3.2.6 Demographic Variables

Demographic variables consisted of age, sex, gender, student status, employment status, and highest level of education. While not explicitly hypothesized in this study, previous research has found differences in adoption behavior between men and women (Jackson et al., 2010). See Appendix F for demographics questions.

3.2.7 Trait-Matched AI Adoption Vignettes

Participants were asked to read through a series of vignettes which they used to anchor their UTAUT questionnaire responses. Scenarios were constructed to be viable in daily life and reasonable for both students and working adults. Principles of trait activation theory were used when designing the vignette scenarios such that they were designed to elicit a moderate level of situational strength to allow variance in behavioral intentions and maximize the influence of personality traits (Tett & Burnett, 2003; Tett & Guterman, 2000). Each vignette was related to the personality and self-concept variables except for propensity to trust. Two vignettes were created to be relatively neutral and common instances of AI use. Vignette research studies have been conducted within the technology acceptance modeling literature to explore .

Two vignette scenarios were also constructed to explore the situational impact of being liable for the consequences of using the decision support AI. These vignettes were manipulated on high and low levels of perceived liability. For example, in the high-liability condition, it was indicated that the individual would be liable for the consequences of any errors that might occur while using the AI, while the low-liability condition indicated that an external entity (e.g., the AI developer) would be liable for the consequences of an error. Half of the sample received the two scenarios manipulated for low liability while the other half received the high liability scenarios. Participants were randomly assigned to the conditions by alternating group placement in Qualtrics. See Appendix G for a list of each of the created vignettes labeled to correspond with their respective trait-matched variables.

3.3 Procedure

Upon following a URL from Prolific to Qualtrics, participants were provided with a consent form that they read and acknowledged to continue with the study. After consenting, participants were asked to respond to a commitment statement referencing the importance of their

role in ensuring data quality (Appendix H). Then, participants provided their demographics and responded to a battery of personality and self-concept measures of interest. They were then asked to read a brief introductory prompt that provided context for AI technology being used to assist humans with decision-making processes. The following section consisted of 22 adoption vignettes. After reading a vignette, participants answered the 13 UTAUT questionnaire items in response to that vignette. This order of procedures occurred for each vignette. The last two vignettes consisted of the high or low liability scenarios depending on which condition the participant was randomly assigned to. The full survey was projected to take approximately 44-60 minutes to complete, however, actual completion time was shorter than expected. After completing the vignettes, participants responded to the effort check (Appendix H) and were then redirected to Prolific to confirm their completion for review and payment. The order of procedures can be found in Figure 3.1.

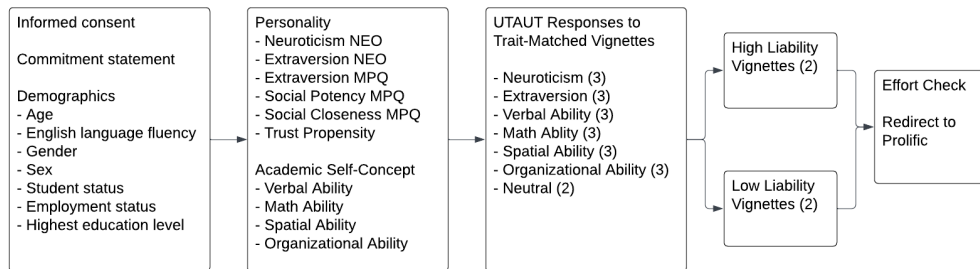


Figure 3.1: Procedure Order and Measures

The following chapter details the results of the present study and is organized into several sections. The first section will describe relevant details related to the data cleaning process. The second section will present the overall descriptive statistics related to the sample responses. The third section will present the statistical analyses conducted to test the proposed hypotheses. Finally, in the fourth section, exploratory analyses that were conducted but were not explicitly hypothesized will be presented.

CHAPTER 4

RESULTS

4.1 Data Cleaning Procedure

As detailed in the procedure and methods, participants responded to the UTAUT measures (i.e., behavioral intention, performance expectancy, effort expectancy, and social influence) for 22 vignettes. No missing data were present in the dataset to account for. Mean aggregates to the UTAUT measures were calculated at several levels to perform the necessary regression analyses: (1) the individual vignette level, (2) the combined trait-matched vignette level, and (3) the experimental liability group level, and (4) the overall level (combining all vignettes except the group assigned liability ones).

4.2 Descriptive Statistics

Descriptive statistics of the overall responses to the hypothesized variables are found in Table 4.1. Bivariate correlations between the primary variables of interest were explored and are found in Table 4.2.

4.3 Hypothesis Testing

The following section will detail the results of the proposed hypothesis testing. The hypotheses were tested with simple linear regression and multiple hierarchical regression models that examined the incremental predictive validity of the select personality traits and ability self-concept measures on the aggregated responses of behavioral intentions to use AI. This approach involved building models in which the core variables of UTAUT predicting overall behavioral intentions to use AI were first entered into the model, and subsequent models included the proposed personality and/or self-concept variables to test

Table 4.1: Descriptive Statistics for Hypothesized Variables

Variable	Mean	SD	Median	Range
Neuroticism NEO	3.04	1.27	3.00	1.00 – 6.00
Extraversion NEO	3.51	1.41	3.50	1.00 – 6.00
Extraversion MPQ	3.07	1.05	3.00	1.00 – 6.00
Social Potency	2.60	1.11	2.50	1.00 – 6.00
Social Closeness	3.27	1.25	3.50	1.00 – 6.00
Trust Propensity	3.81	1.37	4.00	1.00 – 6.00
Self-Concept	5.12	0.71	5.00	2.50 – 6.00
Verbal	5.10	0.70	5.17	2.83 – 6.00
Math	3.80	1.26	4.00	1.00 – 6.00
Spatial	4.33	0.88	4.33	1.17 – 6.00
Organizational	5.12	0.71	5.00	2.50 – 6.00
Performance Expectancy	4.31	0.78	4.39	1.92 – 6.00
Effort Expectancy	4.31	0.78	4.39	1.00 – 6.00
Social Influence	3.97	0.86	4.00	1.00 – 6.00
Behavioral Intention	4.04	0.89	4.08	1.00 – 6.00

Note. $N = 231$. The UTAUT variables are the aggregated average of responses to all vignettes excluding the high and low liability conditions.

incremental validity. When testing the third hypothesis, behavioral intentions and other UTAUT responses were aggregated at the trait-matched vignette levels to test whether individual differences in personality and ability self-concept were more predictive when situationally relevant. ANOVAs were calculated to examine the R^2 increase between models with $p < .05$ as the threshold to support significance. Statistical analyses were carried out using R Version 4.3.1 *stats* (Team, 2023) and *psych* (v2.3.9; Revelle, 2023) packages.

4.3.1 Hypothesis 1 Results

Hypothesis 1 stated the select personality traits in the aggregate would independently account for 8 percent of the variance in behavioral intentions to use AI and would account for 5 percent of the variance over and above the UTAUT core constructs when entered into a hierarchical regression. To test the first part of this hypothesis, neuroticism, extraversion, and propensity to trust were included in a model to predict the overall aggregate of behavioral intentions to use AI. For the second part of the hypothesis, a hierarchical methodology

Table 4.2: Descriptive Statistics for Hypothesized Variables

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Neuroticism NEO	1.00	-	-	-	-	-	-	-	-	-	-	-	-	-	-
2. Extraversion NEO	-0.37	1.00	-	-	-	-	-	-	-	-	-	-	-	-	-
3. Extraversion MPQ	-0.26	0.61	1.00	-	-	-	-	-	-	-	-	-	-	-	-
4. Social Potency MPQ	-0.25	0.37	0.73	1.00	-	-	-	-	-	-	-	-	-	-	-
5. Social Closeness MPQ	-0.14	0.71	0.67	0.33	1.00	-	-	-	-	-	-	-	-	-	-
6. Trust Propensity	-0.21	0.41	0.29	0.15	0.41	1.00	-	-	-	-	-	-	-	-	-
7. Self-Concept (Overall)	-0.32	0.24	0.15	0.12	0.14	0.07	1.00	-	-	-	-	-	-	-	-
8. Verbal	-0.19	0.16	0.05	0.02	0.07	0.13	0.58	1.00	-	-	-	-	-	-	-
9. Math	-0.20	0.11	0.18	0.22	0.03	0.13	0.22	0.21	1.00	-	-	-	-	-	-
10. Spatial	-0.33	0.10	0.16	0.21	0.04	0.12	0.43	0.40	0.53	1.00	-	-	-	-	-
11. Organizational	-0.32	0.29	0.23	0.19	0.17	0.10	0.75	0.33	0.21	0.43	1.00	-	-	-	-
12. Performance Expectancy	-0.09	0.17	0.16	0.13	0.11	0.21	0.17	0.11	0.11	0.13	0.22	1.00	-	-	-
13. Effort Expectancy	-0.16	0.13	0.10	0.14	0.03	0.09	0.37	0.28	0.27	0.34	0.37	0.57	1.00	-	-
14. Social Influence	-0.08	0.20	0.13	0.18	0.08	0.07	0.17	0.09	0.09	0.08	0.22	0.74	0.54	1.00	-
15. Behavioral Intention	-0.07	0.20	0.15	0.17	0.11	0.18	0.19	0.08	0.14	0.16	0.26	0.90	0.61	0.82	1.00

Note. All bolded values are significant at the $p < .05$ level. All bolded and underlined values are significant at the $p < .01$ level. The UTAUT variables are the aggregated average of responses to all vignettes except the high and low liability conditions.

was employed with two models. Model 1 consisted of the core UTAUT variables predicting behavioral intentions to use AI across all vignettes, and Model 2 included the personality variables (i.e., extraversion, neuroticism, and propensity to trust). A significant change in R2 between models 1 and 2 was proposed to indicate support for this hypothesis. For these models, the social potency and social closeness facets of extraversion were omitted to avoid multicollinearity with general extraversion. However, additional post hoc analyses were conducted to further understand whether these facets of extraversion are important for predicting behavioral intentions both in general and in more specific contexts and are detailed later.

A multiple linear regression was first used to predict overall behavioral intentions to use AI with the personality variables (i.e., extraversion, neuroticism, and propensity to trust). This model accounted for a significant amount of variance, $F(3, 227) = 4.12, p < .01, R^2 = .05$. However, in this model, extraversion was the only significant predictor ($t = 2.08, p < .05$) while neuroticism ($t = .18, p = .86$) and propensity to trust ($t = 1.69, p = .09$) were non-significant (Table 4.3).

Table 4.3: Multiple Linear Regression of Personality Variables Predicting Behavioral Intentions

Predictor Variable	β	SE	t	p-value
Intercept	3.37	0.29	11.73	<.001
Neuroticism NEO	0.01	0.05	0.18	0.86
Extraversion NEO	0.10	0.05	2.08	<.05
Trust Propensity	0.08	0.05	1.69	0.09

Note. $F(3, 227) = 4.12, p < .01, R^2 = 0.05, R_{adj.}^2 = 0.04$

Next a hierarchical design consisting of two models was used to test the incremental predictive validity of the selected personality traits over and above the core UTAUT variables. Model 1 predicted overall behavioral intentions to use AI from the overall UTAUT variables (i.e., performance expectancy, effort expectancy, and social influence) and accounted for a significant amount of variance, $F(3, 227) = 519.8, p < .001, R^2 = .87$. In

Model 1, performance expectancy ($t = 17.06, p < .001$), effort expectancy ($t = 2.39, p < .05$), and social influence ($t = 9.00, p < .001$) were all significant predictors. Model 2 predicted overall behavioral intentions to use AI from the UTAUT variables and the personality traits and accounted for a significant amount of variance $F(6, 224) = 261.3, p < .001, R^2 = .88$. In Model 2, performance expectancy ($t = 16.44, p < .001$), effort expectancy ($t = 2.58, p < .05$), and social influence ($t = 8.71, p < .001$) were all significant predictors, while neuroticism ($t = 1.62, p = .11$), extraversion ($t = 1.10, p = .27$), and propensity to trust ($t = .61, p = .54$) were not significant predictors (Table 4.4). An ANOVA was calculated between Model 1 and Model 2 to examine the R^2 increase between these two models. Model 1 accounted for 87% of the variance and Model 2 accounted for 88% of the variance ($\Delta R^2 = .01$) $F(3, 224) = 1.23, p = .30$, and was not significant.

Table 4.4: Hierarchical Regression of Personality's Increment Over UTAUT

Predictor Variable	Model 1				Model 2			
	β	SE	t	p-value	β	SE	t	p-value
Intercept	-0.82	0.15	-5.47	<.001	-1.01	0.18	-5.59	<.001
Performance Expectancy	0.72	0.04	17.06	<.001	0.71	0.04	16.44	<.001
Effort Expectancy	0.09	0.04	2.39	<.05	0.10	0.04	2.58	<.05
Social Influence	0.33	0.04	9.00	<.001	0.33	0.04	8.71	<.001
Neuroticism NEO					0.03	0.02	1.62	0.11
Extraversion NEO					0.02	0.02	1.10	0.27
Trust Propensity					0.01	0.02	0.61	0.54

Note. Model 1 $F(3, 227) = 519.8, p < .001, R^2 = 0.87, R^2_{adj.} = 0.87$. Model 2 $F(6, 224) = 261.3, p < .001, R^2 = 0.88, R^2_{adj.} = 0.87$.

Hypothesis 1 stated that the personality traits in the aggregate would account for 8% of the variance in behavioral intentions to use AI, and the first regression analysis found that the personality traits significantly accounted for 5% of the variance independently, 3% less than expected. Hypothesis 1 also stated that the aggregated personality traits would account for 5% of the variance in behavioral intentions to use AI over and above the core UTAUT constructs. The hierarchical regression analysis did not find a significant change in R^2 between Model 1 and Model 2; thus Hypothesis 1 was not supported.

4.3.2 Hypothesis 2 Results

Hypothesis 2 stated the ability self-concept in the aggregate would independently account for 10 percent of the variance in behavioral intentions to use AI and would account for 8 percent of the variance over and above the UTAUT core constructs when entered into a hierarchical regression. This hypothesis was tested in the same manner as Hypothesis 1 but replacing the personality variables with the ability self-concept variables. A multiple linear regression was used to predict overall behavioral intentions to use AI with the ability self-concept variables (i.e., verbal ability, math ability, spatial ability, organizational ability). This model accounted for a significant amount of variance, $F(3, 226) = 4.51, p < .01, R^2 = .07$. However, in this model, organizational self-concept was the only significant predictor ($t = 3.29, p < .01$) while verbal self-concept ($t = -.28, p = .78$), math self-concept ($t = 1.08, p = .28$), and spatial self-concept ($t = .25, p = .80$) were non-significant (Table 4.5).

Table 4.5: Multiple Linear Regression of Self-Concept Variables Predicting Behavioral Intention

Predictor Variable	β	SE	t	p-value
Intercept	2.76	0.46	6.04	<.001
Verbal	-0.03	0.09	-0.28	0.78
Math	0.06	0.05	1.08	0.28
Spatial	0.02	0.09	0.25	0.80
Organizational	0.24	0.07	3.29	<.001

Note. $F(4, 226) = 4.51, p < .01, R^2 = 0.07, R^2_{adj.} = 0.06$.

Next the hierarchical design consisting of two models was used to test the incremental predictive validity of the ability self-concept over and above the core UTAUT variables. Model 1 was constructed and calculated identically to Model 1 used in Hypothesis 1 which yielded the same results here. Model 2 predicted overall behavioral intentions to use AI from the UTAUT variables and ability self-concept and accounted for a significant amount of variance $F(7, 223) = 227.3, p < .001, R^2 = .88$. In Model 2, performance expectancy

($t = 17.20, p < .001$), social influence ($t = 8.71, p < .001$), and verbal self-concept ($t = -2.32, p < .05$) were all significant predictors, while effort expectancy ($t = 1.91, p = .06$), math self-concept ($t = .56, p = .58$), spatial self-concept ($t = 1.13, p = .26$), and organizational self-concept ($t = .92, p = .36$) were not significant predictors. An ANOVA was calculated between Model 1 and Model 2 to examine the R^2 increase between these two models. Model 1 accounted for 87% of the variance and Model 2 accounted for 88% of the variance ($\Delta R^2 = .01$) $F(4, 223) = 1.88, p = .11$, and was not significant (Table 4.6).

Table 4.6: Hierarchical Regression of Personality's Increment Over UTAUT

Predictor Variable	Model 1				Model 2			
	β	SE	t	p-value	β	SE	t	p-value
Intercept	-0.82	0.15	-5.47	<.001	-0.69	0.19	-3.55	<.001
Performance Expectancy	0.72	0.04	17.06	<.001	0.72	0.04	17.20	<.001
Effort Expectancy	0.09	0.04	2.39	<.05	0.08	0.04	1.91	0.06
Social Influence	0.33	0.04	9.00	<.001	0.33	0.04	9.01	<.001
Verbal					-0.08	0.03	-2.32	<.05
Math					0.01	0.02	0.56	0.58
Spatial					0.04	0.03	1.13	0.26
Organizational					0.02	0.03	0.92	0.36

Note. Model 1 $F(3, 227) = 519.8, p < .001, R^2 = 0.87, R^2_{adj.} = 0.87$. Model 2 $F(7, 223) = 227.3, p < .001, R^2 = 0.88, R^2_{adj.} = 0.87$.

Hypothesis 2 stated that ability self-concept in the aggregate would account for 10% of the variance in behavioral intentions to use AI, and the first regression analysis found that the self-concept scores significantly accounted for 7% of the variance independently, 3% less than expected. Hypothesis 2 also stated that the aggregated ability self-concept would account for 8% of the variance in behavioral intentions to use AI over and above the core UTAUT constructs. The hierarchical regression analysis did not find a significant change in R^2 between Model 1 and Model 2. These results indicate that Hypothesis 2 was not supported.

4.3.3 Hypothesis 3 Results

Lastly, Hypothesis 3 stated that personality (i.e., extraversion and neuroticism) and ability self-concept (i.e., math verbal, spatial, and organizational) would independently account

for 13-15 percent of the variance in behavioral intentions to use AI and 10-13 percent of the variance over and above the UTAUT core constructs when the variable corresponded with the trait-matched vignette use domain. To test this hypothesis, six hierarchical regression analyses were conducted predicting behavioral intentions to use AI at the various trait-matched aggregate levels. Each hierarchical regression methodology employed the following model structures: Model 1 consisted of the core UTAUT variables, Model 2 added the relevant personality trait or ability self-concept, and Model 3 added all other personality and ability self-concept variables hypothesized to be “non-relevant.”

Starting with the personality traits, a multiple linear regression was used to predict behavioral intentions to use AI in the extraversion-matched vignettes. First, a simple linear regression was conducted predicting behavioral intentions with only extraversion. This model did not account for a significant amount of variance $F(1, 229) = 3.48, p = .06, R^2 = .01$ and extraversion was not a significant predictor ($t = 1.86, p = .06$) (Table 4.7).

Table 4.7: Simple Linear Regression of Extraversion Predicting Matched Behavioral Intentions

Predictor Variable	β	SE	t	p-value
Intercept	2.88	0.21	13.44	<.001
Extraversion	0.11	0.06	1.86	0.06

Note. $F(1, 229) = 3.48, p = .06, R^2 = 0.01, R^2_{adj.} = 0.01$.

Beginning the hierarchical methodology, Model 1 predicted behavioral intentions in the extraversion-matched vignettes from the extraversion-matched UTAUT variables and accounted for a significant amount of variance $F(3, 227) = 347.9, p < .001, R^2 = .82$. In Model 1, performance expectancy ($t = 12.61, p < .001$), effort expectancy ($t = 2.63, p < .01$) and social influence ($t = 8.81, p < .001$) were all significant predictors. Model 2 predicted behavioral intentions to use AI (extraversion) from the UTAUT variables and extraversion and accounted for a significant amount of variance in behavioral intentions

$F(4, 226) = 261.4, p < .001. R^2 = .82$. In Model 2, performance expectancy ($t = 12.62, p < .001$), effort expectancy ($t = 2.52, p < .05$), and social influence ($t = 8.77, p < .001$) were significant predictors while extraversion ($t = 1.07, p = .29$) was not a significant predictor. Model 3 predicted behavioral intentions to use AI (extraversion) from the UTAUT variables, extraversion, and other personality/self-concept variables (i.e., neuroticism, propensity to trust, verbal self-concept, math self-concept, spatial self-concept, and organizational self-concept) and accounted for a significant amount of variance $F(10, 220) = 114.3, p < .001. R^2 = 0.84$. In Model 3, performance expectancy ($t = 12.32, p < .001$), effort expectancy ($t = 2.62, p < .01$), social influence ($t = 8.75, p < .001$), neuroticism ($t = 2.27, p < .05$), trust propensity ($t = 2.60, p < .05$), verbal self-concept ($t = -2.85, p < .01$), and organizational self-concept ($t = 2.30, p < .05$) were significant predictors while extraversion ($t = .40, p = .69$), math self-concept ($t = -0.26, p = .80$), and spatial self-concept ($t = 1.26, p = .21$) were not significant predictors (Table 4.8). An ANOVA was calculated between the three models to examine the R^2 increase between them. Model 1 accounted for 82% of the variance and Model 2 accounted for 82% of the variance ($\Delta R^2 = .00$), $F(1, 226) = 1.22, p = .27$, and was not significant. Model 2 accounted for 82% of the variance and Model 3 accounted for 84% of the variance ($\Delta R^2 = .02$) $F(6, 220) = 3.70, p < .01$, and was significant. This analysis was also conducted for the MPQ extraversion facets and yielded similar results.

The next hierarchical regression analysis predicted behavioral intentions for the neuroticism-matched vignettes. A simple linear regression was conducted predicting behavioral intentions with only neuroticism. This model did not account for a significant amount of variance $F(1, 229) = 0.14, p = 0.71. R^2 < .001$ and neuroticism was not a significant predictor ($t = -0.37, p = 0.71$) (Table 4.9).

For the hierarchical methodology, Model 1 predicted behavioral intentions in the neuroticism-matched vignettes from the neuroticism-matched UTAUT variables and accounted for a significant amount of variance $F(3, 227) = 485.5, p < .001. R^2 = .87$. In Model 1, per-

Table 4.8: Hierarchical Regression for Extraversion-Matched Vignettes

Predictor Variable	Model 1			Model 2			Model 3		
	β	SE	t	β	SE	t	β	SE	t
Intercept	-0.65	0.16	-3.98	-0.72	0.18	-4.10	-1.07	0.35	-3.06
Performance Expectancy	0.59	0.05	12.61	0.59	0.05	12.62	0.57	0.05	12.32
Effort Expectancy	0.10	0.04	2.63	0.10	0.04	2.52	0.11	0.04	2.63
Social Influence	0.42	0.05	8.81	0.42	0.05	8.77	0.42	0.05	8.75
Extraversion NEO				0.03	0.02	1.07	0.01	0.03	0.40
Neuroticism NEO							0.07	0.03	2.27
Trust							0.07	0.03	2.60
Verbal							-0.15	0.05	-2.85
Math							-0.01	0.03	-0.26
Spatial							0.06	0.05	1.26
Organizational							0.10	0.04	2.30

Note. Model 1 $F(3, 227) = 347.9, p < .001, R^2 = 0.82, R^2_{adj.} = 0.82$. Model 2 $F(4, 226) = 261.4, p < .001, R^2 = 0.82, R^2_{adj.} = 0.82$. Model 3 $F(10, 220) = 114.3, p < .001, R^2 = 0.84, R^2_{adj.} = 0.83$.

Table 4.9: Simple Linear Regression of Neuroticism Predicting Matched Behavioral Intentions

Predictor Variable	β	SE	t	p-value
Intercept	3.53	0.20	17.25	<.001
Neuroticism	-0.02	0.06	-0.37	0.71

Note. $F(1, 229) = 0.14, p = .71, R^2 < 0.001, R^2_{adj.} < 0.001$.

formance expectancy ($t = 15.11, p < .001$), effort expectancy ($t = 2.35, p < .05$) and social influence ($t = 10.09, p < .001$) were all significant predictors. Model 2 predicted behavioral intentions to use AI (neuroticism) from the UTAUT variables and neuroticism and accounted for a significant amount of variance in behavioral intentions $F(4, 226) = 362.6, p < .001, R^2 = .87$. In Model 2, performance expectancy ($t = 15.07, p < .001$), effort expectancy ($t = 2.34, p < .05$), and social influence ($t = 10.06, p < .001$) were significant predictors while neuroticism ($t = .04, p = .97$) was not a significant predictor. Model 3 predicted behavioral intentions to use AI (neuroticism) from the UTAUT variables, neuroticism, and other personality/self-concept variables (i.e., extraversion, propensity to trust, verbal self-concept, math self-concept, spatial self-concept, and organizational self-concept) and accounted for a significant amount of variance $F(10, 220) = 148.1, p < .001, R^2 = .87$. In Model 3, performance expectancy ($t = 14.58, p < .001$), effort ex-

pectancy ($t = 2.80, p < .01$), social influence ($t = 9.73, p < .001$), and verbal self-concept ($t = -2.51, p < .05$) were significant predictors while neuroticism ($t = .47, p = .64$), extraversion ($t = 1.55, p = .12$), trust propensity ($t = .36, p = .72$), math self-concept ($t = -.29, p = .77$), spatial self-concept ($t = 1.05, p = .29$), and organizational self-concept ($t = -.46, p = .64$) were not significant predictors (Table 4.10). An ANOVA was calculated between the three models to examine the R^2 increase between them. Model 1 accounted for 87% of the variance and Model 2 accounted for 87% of the variance ($\Delta R^2 < .01$) $F(1, 226) = .001, p = .97$, and was not significant. Model 2 accounted for 87% of the variance and Model 3 accounted for 87% of the variance ($\Delta R^2 < .01$) $F(6, 220) = 1.55, p = .16$, and was not significant.

Table 4.10: Hierarchical Regression for Neuroticism-Matched Vignettes

Predictor Variable	Model 1			Model 2			Model 3		
	β	SE	t	β	SE	t	β	SE	t
Intercept	-0.56	0.14	-4.04	-0.56	0.16	-3.47	-0.29	0.30	-0.97
Performance Expectancy	0.61	0.04	15.11	0.61	0.04	15.07	0.60	0.04	14.58
Effort Expectancy	0.09	0.04	2.35	0.09	0.04	2.34	0.11	0.04	2.80
Social Influence	0.40	0.04	10.09	0.40	0.04	10.06	0.39	0.04	9.73
Neuroticism NEO				0.00	0.02	0.04	0.01	0.03	0.47
Extraversion NEO							0.04	0.02	1.55
Trust							0.01	0.02	0.36
Verbal							-0.12	0.05	-2.51
Math							-0.01	0.03	-0.29
Spatial							0.05	0.04	1.05
Organizational							-0.02	0.04	-0.46

Note. Model 1 $F(3, 227) = 485.5, p < .001, R^2 = 0.87, R^2_{adj.} = 0.86$. Model 2 $F(4, 226) = 362.6, p < .001, R^2 = 0.87, R^2_{adj.} = 0.86$. Model 3 $F(10, 220) = 148.1, p < .001, R^2 = 0.87, R^2_{adj.} = 0.86$.

This section provides results for hierarchical regression analyses examining the ability self-concept matched vignettes. Beginning with self-concept for verbal ability, a simple linear regression was conducted predicting behavioral intentions to use AI in verbal-matched vignettes with only verbal self-concept. This model did not account for a significant amount of variance $F(1, 229) = .002, p = .96, R^2 < .001$, and verbal self-concept was not a significant predictor ($t = .05, p = .96$) (Table 4.11).

As for the hierarchical methodology, Model 1 predicted behavioral intentions in the

Table 4.11: Simple Linear Regression of Verbal Self-Concept Predicting Matched Behavioral Intentions

Predictor Variable	β	SE	t	p-value
Intercept	4.14	0.58	7.20	<.001
Verbal	0.01	0.11	0.05	0.96

Note. $F(1, 229) = 0.002, p = .96, R^2 < 0.001, R^2_{adj.} < 0.001$.

verbal-matched vignettes from the verbal-matched UTAUT variables and accounted for a significant amount of variance $F(3, 227) = 323.7, p < .001, R^2 = .81$. In Model 1, performance expectancy ($t = 14.40, p < .001$) and social influence ($t = 9.07, p < .001$) were significant predictors, while effort expectancy ($t = 1.68, p < .001$) was not a significant predictor. Model 2 incorporated the UTAUT variables and verbal self-concept and accounted for a significant amount of variance in behavioral intentions $F(4, 226) = 243.3, p < .001, R^2 = .81$. In Model 2, performance expectancy ($t = 14.17, p < .001$) and social influence ($t = 9.01, p < .001$) were significant predictors while effort expectancy ($t = 1.96, p = .05$) and verbal self-concept ($t = -1.12, p = .26$) were not significant predictors. Model 3 then included the UTAUT variables, verbal self-concept, and the remaining personality/self-concept variables and accounted for a significant amount of variance $F(10, 220) = 99.76, p < .001, R^2 = .82$. In Model 3, performance expectancy ($t = 13.78, p < .001$), social influence ($t = 8.91, p < .001$), and math self-concept ($t = 2.09, p = .04$) were significant predictors while effort expectancy ($t = 1.31, p = .19$), verbal self-concept ($t = -1.21, p = .23$), neuroticism ($t = 1.28, p = .20$), extraversion ($t = -.10, p = .92$), propensity to trust ($t = 1.74, p = .08$), spatial self-concept ($t = -.65, p = .51$), and organizational self-concept ($t = .73, p = .46$) were not significant predictors (Table 4.12). An ANOVA was calculated between the three models to examine the R^2 increase between them. Model 1 accounted for 81% of the variance and Model 2 accounted for 81% of the variance ($\Delta R^2 = .001$) $F(1, 226) = 1.28, p = .26$, and was not significant. Model 2 accounted for 81% of the variance and Model 3 accounted for

82% of the variance ($\Delta R^2 = .01$) $F(6, 220) = 1.57, p = .16$, and was not significant.

Table 4.12: Hierarchical Regression for Verbal-Matched Vignettes

Predictor Variable	Model 1			Model 2			Model 3		
	β	SE	t	β	SE	t	β	SE	t
Intercept	-0.77	0.22	-3.57	-0.54	0.30	-1.80	-0.91	0.37	-2.49
Performance Expectancy	0.69	0.05	14.40	0.68	0.05	14.17	0.68	0.05	13.78
Effort Expectancy	0.09	0.05	1.68	0.11	0.06	1.96	0.08	0.06	1.31
Social Influence	0.35	0.04	9.07	0.35	0.04	9.01	0.36	0.04	8.91
Verbal				-0.06	0.05	-1.12	-0.07	0.06	-1.21
Neuroticism NEO							0.04	0.03	1.28
Extraversion NEO							0.00	0.03	-0.10
Trust							0.05	0.03	1.74
Math							0.07	0.03	2.09
Spatial							-0.03	0.05	-0.65
Organizational							0.03	0.05	0.73

Note. Model 1 $F(3, 227) = 323.7, p < .001, R^2 = 0.81, R^2_{adj.} = 0.81$. Model 2 $F(4, 226) = 243.3, p < .001, R^2 = 0.81, R^2_{adj.} = 0.81$. Model 3 $F(10, 220) = 99.76, p < .001, R^2 = 0.82, R^2_{adj.} = 0.81$.

Next, a simple linear regression was conducted predicting behavioral intentions to use AI in math-matched vignettes with only math self-concept. This model did not account for a significant amount of variance $F(1, 229) = 1.23, p < .27, R^2 = .005$ and math self-concept was not a significant predictor ($t = 1.11, p = .27$) (Table 4.13).

Table 4.13: Simple Linear Regression of Math Self-Concept Predicting Matched Behavioral Intentions

Predictor Variable	β	SE	t	p-value
Intercept	4.33	0.20	21.48	<.001
Math	0.06	0.05	1.11	0.27

Note. $F(1, 229) = 1.23, p = .27, R^2 < 0.005, R^2_{adj.} < 0.001$.

As for the hierarchical methodology, Model 1 predicted behavioral intentions in the math-matched vignettes from the math-matched UTAUT variables and accounted for a significant amount of variance $F(3, 227) = 374, p < .001, R^2 = .83$. In Model 1, performance expectancy ($t = 16.31, p < .001$), effort expectancy ($t = 3.79, p < .001$), and social influence ($t = 9.46, p < .001$) were significant predictors. Model 2 incorporated the UTAUT variables and math self-concept and accounted for a significant amount of variance in behavioral intentions $F(4, 226) = 280.8, p < .001, R^2 = .83$. In Model 2, performance

expectancy ($t = 16.26, p < .001$), effort expectancy ($t = 3.23, p < .01$), and social influence ($t = 9.47, p < .001$) were significant predictors while self-concept of math ability ($t = 1.01, p = .31$) was not a significant predictor. Model 3 then included the UTAUT variables, math self-concept, and the remaining personality/self-concept variables and accounted for a significant amount of variance $F(10, 220) = 112.7, p < .001, R^2 = .84$. In Model 3, performance expectancy ($t = 15.61, p < .001$), effort expectancy ($t = 3.21, p < .01$), and social influence ($t = 9.33, p < .001$) were significant predictors while math self-concept ($t = .71, p = .47$), neuroticism ($t = 1.34, p = .18$), extraversion ($t = .17, p = .87$), propensity to trust ($t = 1.19, p = .24$), verbal self-concept ($t = -.83, p = .41$), spatial self-concept ($t = .98, p = .33$), and organizational self-concept ($t = -.96, p = .34$) were not significant predictors (Table 4.14). An ANOVA was calculated between the three models to examine the R^2 increase between them. Model 1 accounted for 83% of the variance and Model 2 accounted for 83% of the variance ($\Delta R^2 < .001$), $F(1, 226) = 1.02, p = .31$, and was not significant. Model 2 accounted for 83% of the variance and Model 3 accounted for 84% of the variance ($\Delta R^2 = .004$), $F(6, 220) = .94, p = .46$, and was not significant.

Table 4.14: Hierarchical Regression for Math-Matched Vignettes

Predictor Variable	Model 1			Model 2			Model 3		
	β	SE	t	β	SE	t	β	SE	t
Intercept	-0.79	0.18	-4.35	-0.84	0.19	-4.47	-0.92	0.28	-3.32
Performance Expectancy	0.65	0.04	16.31	0.66	0.04	16.26	0.66	0.04	15.61
Effort Expectancy	0.16	0.04	3.79	0.14	0.04	3.23	0.15	0.05	3.21
Social Influence	0.34	0.04	9.46	0.34	0.04	9.47	0.34	0.04	9.33
Math				0.02	0.02	1.01	0.02	0.03	0.71
Neuroticism NEO							0.03	0.02	1.34
Extraversion NEO							0.00	0.02	0.17
Trust							0.03	0.02	1.19
Verbal							-0.03	0.04	-0.83
Spatial							0.04	0.04	0.98
Organizational							-0.03	0.04	-0.96

Note. Model 1 $F(3, 227) = 374, p < .001, R^2 = 0.83, R^2_{adj.} = 0.83$. Model 2 $F(4, 226) = 280.8, p < .001, R^2 = 0.83, R^2_{adj.} = 0.83$. Model 3 $F(10, 220) = 112.7, p < .001, R^2 = 0.84, R^2_{adj.} = 0.83$.

Next, a simple linear regression was conducted predicting behavioral intentions to use AI in spatial-matched vignettes with only spatial self-concept. This model did not account

for a significant amount of variance $F(1, 229) = 2.52, p = .11, R^2 = .01$ and spatial self-concept was not a significant predictor ($t = 1.588, p = .11$) (Table 4.15).

Table 4.15: Simple Linear Regression of Spatial Self-Concept Predicting Matched Behavioral Intentions

Predictor Variable	β	SE	t	p-value
Intercept	3.20	0.38	8.36	<.001
Spatial	0.14	0.09	1.59	0.11

Note. $F(1, 229) = 2.52, p = .11, R^2 < 0.01, R^2_{adj} < 0.006$.

As for the hierarchical methodology, Model 1 predicted behavioral intentions in the spatial-matched vignettes from the spatial-matched UTAUT variables and accounted for a significant amount of variance $F(3, 227) = 296.7, p < .001, R^2 = .80$. In Model 1, performance expectancy ($t = 11.68, p < .001$), effort expectancy ($t = 2.29, p < .05$), and social influence ($t = 8.24, p < .001$) were significant predictors. Model 2 incorporated the UTAUT variables and spatial self-concept and accounted for a significant amount of variance in behavioral intentions $F(4, 226) = 223.9, p < .001, R^2 = .80$. In Model 2, performance expectancy ($t = 11.78, p < .001$) and social influence ($t = 8.33, p < .001$) were significant predictors while effort expectancy ($t = 1.81, p = .09$) and spatial self-concept ($t = 1.39, p = .16$) were not significant predictors. Model 3 then included the UTAUT variables, spatial self-concept, and the remaining personality/self-concept variables and accounted for a significant amount of variance $F(10, 220) = 92.09, p < .001, R^2 = .81$. In Model 3, performance expectancy ($t = 11.38, p < .001$), effort expectancy ($t = 1.97, p < .05$), social influence ($t = 8.39, p < .001$), and verbal self-concept ($t = -2.35, p < .05$) were significant predictors while spatial self-concept ($t = 1.57, p = 0.12$), neuroticism ($t = 1.40, p = .16$), extraversion ($t = .02, p = .98$), propensity to trust ($t = 1.63, p = .10$), math self-concept ($t = .42, p = .68$), and organizational self-concept ($t = .66, p = .51$) were not significant predictors (Table 4.16). An ANOVA was calculated between the three models to examine the R^2 increase between them. Model 1 accounted for 80% of the vari-

ance and Model 2 accounted for 80% of the variance ($\Delta R^2 = .002$), $F(1, 226) = 1.98$, $p = .16$, and was not significant. Model 2 accounted for 80% of the variance and Model 3 accounted for 81% of the variance ($\Delta R^2 = .009$), $F(6, 220) = 1.64$, $p = .14$, and was not significant.

Table 4.16: Hierarchical Regression for Spatial-Matched Vignettes

Predictor Variable	Model 1			Model 2			Model 3		
	β	SE	t	β	SE	t	β	SE	t
Intercept	-0.99	0.19	-5.15	-1.17	0.23	-5.02	-1.16	0.37	-3.15
Performance Expectancy	0.61	0.05	11.68	0.62	0.05	11.78	0.61	0.05	11.38
Effort Expectancy	0.12	0.05	2.29	0.10	0.06	1.71	0.11	0.06	1.97
Social Influence	0.40	0.05	8.24	0.41	0.05	8.33	0.41	0.05	8.39
Spatial				0.06	0.04	1.39	0.08	0.05	1.57
Neuroticism NEO							0.04	0.03	1.40
Extraversion NEO							0.00	0.03	0.03
Trust							0.05	0.03	1.63
Math							0.01	0.03	0.42
Verbal							-0.13	0.05	-2.35
Organizational							0.03	0.05	0.66

Note. Model 1 $F(3, 227) = 296.7$, $p < .001$, $R^2 = 0.80$, $R^2_{adj.} = 0.80$. Model 2 $F(4, 226) = 223.9$, $p < .001$, $R^2 = 0.80$, $R^2_{adj.} = 0.80$. Model 3 $F(10, 220) = 92.09$, $p < .001$, $R^2 = 0.81$, $R^2_{adj.} = 0.80$.

Next, a simple linear regression was conducted predicting behavioral intentions to use AI in organizational-matched vignettes with only organizational self-concept. This model accounted for a significant amount of variance $F(1, 229) = 4.48$, $p < .05$. $R^2 = .02$ and organizational self-concept was a significant predictor ($t = 2.12$, $p < .05$) (Table 4.17).

Table 4.17: Simple Linear Regression of Organizational Self-Concept Predicting Matched Behavioral Intentions

Predictor Variable	β	SE	t	p-value
Intercept	3.37	0.41	8.15	<.001
Organizational	0.18	0.09	2.12	<.05

Note. $F(1, 229) = 4.48$, $p = .05$, $R^2 = 0.02$, $R^2_{adj.} < 0.01$.

As for the hierarchical methodology, Model 1 predicted behavioral intentions in the organizational-matched vignettes from the organizational-matched UTAUT variables and accounted for a significant amount of variance $F(3, 227) = 407.9$, $p < .001$, $R^2 = .84$. In Model 1, performance expectancy ($t = 15.55$, $p < .001$), and social influence ($t =$

8.82, $p < .001$) were significant predictors while effort expectancy ($t = 1.77, p = .08$) was not a significant predictor. Model 2 incorporated the UTAUT variables and organizational self-concept and accounted for a significant amount of variance in behavioral intentions $F(4, 226) = 305.6, p < .001, R^2 = .84$. In Model 2, performance expectancy ($t = 15.56, p < .001$) and social influence ($t = 8.80, p < .001$) were significant predictors while effort expectancy ($t = 1.45, p = .15$) and organizational self-concept ($t = .79, p = .43$) were not significant predictors. Model 3 then included the UTAUT variables, spatial self-concept, and the remaining personality/self-concept variables and accounted for a significant amount of variance $F(10, 220) = .85, p < .001, R^2 = .85$. In Model 3, performance expectancy ($t = 15.58, p < .001$) social influence ($t = 8.28, p < .001$), and extraversion ($t = 2.04, p < .05$) were significant predictors while effort expectancy ($t = 1.51, p = .13$), organizational self-concept ($t = .65, p = .52$), neuroticism ($t = 1.44, p = .15$), propensity to trust ($t = -.33, p = .74$), math self-concept ($t = .40, p = .69$), verbal self-concept ($t = -1.45, p = .15$), and spatial self-concept ($t = .56, p = .57$) were not significant predictors (Table 4.18). An ANOVA was calculated between the three models to examine the R^2 increase between them. Model 1 accounted for 84% of the variance and Model 2 accounted for 84% of the variance ($\Delta R^2 = .001$), $F(1, 226) = .62, p = .43$, and was not significant. Model 2 accounted for 84% of the variance and Model 3 accounted for 85% of the variance ($\Delta R^2 = .005$) $F(6, 220) = 1.18, p = .32$, and was not significant.

The first part of Hypothesis 3 stated that, when predicting behavioral intentions for their respective trait-matched vignettes, the personality and ability self-concept variables would independently account for 13-15 percent of the variance. The simple linear regressions calculated to test this found that these variables only accounted for 0 – 2 percent of the variance in behavioral intentions. The second part of Hypothesis 3 stated that the individual difference variables would account for 10 – 13 percent of the variance in behavioral intentions over and above the core UTAUT variables within their respective matched contexts. The hierarchical regression analyses conducted to test this found that the relevant

Table 4.18: Hierarchical Regression for Organizational-Matched Vignettes

Predictor Variable	Model 1			Model 2			Model 3		
	β	SE	t	β	SE	t	β	SE	t
Intercept	-0.83	0.20	-4.19	-0.91	0.23	-4.03	-0.98	0.34	-2.92
Performance Expectancy	0.67	0.04	15.55	0.67	0.04	15.56	0.68	0.04	15.58
Effort Expectancy	0.08	0.05	1.77	0.07	0.05	1.45	0.08	0.05	1.51
Social Influence	0.40	0.04	8.82	0.40	0.04	8.80	0.38	0.05	8.28
Organizational				0.03	0.04	0.79	0.03	0.04	0.65
Neuroticism NEO							0.04	0.03	1.44
Extraversion NEO							0.05	0.03	2.04
Trust							-0.01	0.03	-0.33
Math							0.01	0.03	0.40
Verbal							-0.07	0.05	-1.45
Spatial							0.03	0.05	0.56

Note. Model 1 $F(3, 227) = 407.9, p < .001, R^2 = 0.84, R^2_{adj.} = 0.84$. Model 2 $F(4, 226) = 305.6, p < .001, R^2 = 0.84, R^2_{adj.} = 0.84$. Model 3 $F(10, 220) = 123.5, p < .001, R^2 = 0.85, R^2_{adj.} = 0.84$.

traits accounted for less than 1 percent of the variance over and above the UTAUT variables and were not significant. Hypothesis 3 was not supported.

4.4 Exploratory/Supplementary Analyses

4.4.1 Perceptions of Liability

As detailed in the procedure, additional vignettes were developed and manipulated on level of perceived liability. Participants were then randomly assigned to either the high liability or low liability vignette conditions. Descriptive statistics between the two liability groups are provided in Table 4.19.

Four independent samples T-tests were conducted to examine the differences in UTAUT responses between the two experimental groups. The 115 participants who received the high-liability vignettes ($M = 3.06, SD = 1.29$) compared to the 116 participants who received the low-liability vignettes ($M = 4.03, SD = 1.27$) had significantly lower behavioral intention scores, $t(228.8) = 5.81, p < .001$. The effect size, as measured by Cohen's d , indicated a large effect ($d = .76$) The high liability group ($M = 3.41, SD = 1.19$) compared to the low liability group ($M = 4.26, SD = 1.15$) had significantly lower performance expectancy scores, $t(228.68) = 5.52, p < .001$. The effect size indicated

Table 4.19: Hierarchical Regression for Organizational-Matched Vignettes

Variable	N	Mean	SD	Median	Min	Max
Low Liability Condition						
Performance Expectancy	116	4.26	1.15	4.25	1.00	6.00
Effort Expectancy	116	4.43	1.06	4.50	1.00	6.00
Social Influence	116	3.69	1.10	3.75	1.00	6.00
Behavioral Intention	116	4.03	1.27	4.00	1.00	6.00
High Liability Condition						
Performance Expectancy	115	3.41	1.19	3.50	1.00	6.00
Effort Expectancy	115	4.01	1.01	4.12	1.25	6.00
Social Influence	115	2.97	1.18	3.00	1.00	6.00
Behavioral Intention	115	3.06	1.29	3.00	1.00	6.00

Note. The UTAUT variables are the mean aggregated average of responses to the two high and low liability vignettes.

a large effect ($d = .73$). The high liability group ($M = 4.01, SD = 1.01$) compared to the low liability group ($M = 4.43, SD = 1.06$) had significantly lower effort expectancy scores, $t(228.7) = 3.04, p < .01$. The effect size indicated a small effect ($d = .40$). Lastly, the high liability group ($M = 2.97, SD = 1.18$) compared to the low liability group ($M = 3.69, SD = 1.10$) had significantly lower social influence scores, $t(227.36) = 4.82, p < .001$. The effect size indicated a medium effect ($d = .63$). Overall, the mean scores for behavioral intentions, performance expectancy, effort expectancy, and social influence were significantly lower for those in the high liability group compared to those in the low liability group.

4.4.2 Individual Differences as Distal Predictors

The results of the present hypotheses were theoretically sound as the individual differences as predictors are likely distal from behavioral intentions and more proximal to attitude development. For this reason, additional multiple regression analyses were conducted to better understand the impact of the individual difference variables on the UTAUT attitudes. Beginning with performance expectancy, a hierarchical regression analysis was conducted to examine the predictive validity of the personality and self-concept. The effort expectancy variable has been found to predict performance expectancy so exam-

ining whether the individual difference variables incremented over and above effort expectancy was of interest. First, a simple linear regression was conducted predicting overall performance expectancy scores with effort expectancy. This model accounted for a significant amount of variance $F(1, 229) = 113, p < .001, R^2 = .33$ with effort expectancy as a significant predictor ($t = 10.63, p < .001$). The second model entered propensity to trust due to it being found to correlate most with performance expectancy ($r = .21$) compared to the other independent variables. Model 2 accounted for a significant amount of variance, $F(2, 228) = 62.73, p < .001, R^2 = .36$ with both effort expectancy ($t = 10.48, p < .001$) and propensity to trust ($t = 2.95, p < .01$) as significant predictors. Lastly, to check whether the other individual difference variables accounted for additional significant variance, the remaining independent variables were entered into Model 3. Model 3 accounted for a significant amount of variance in performance expectancy $F(8, 222) = 16.19, p < .001, R^2 = .37$ with effort expectancy ($t = 9.93, p < .001$) and propensity to trust ($t = 2.68, p < .01$) as significant predictors, while neuroticism ($t = .33, p = .76$), extraversion ($t = .67, p = .50$), verbal self-concept ($t = -.86, p = .39$), math self-concept ($t = -.59, p = .56$), spatial self-concept ($t = -.96, p = .34$), and organizational self-concept ($t = .48, p = .63$) were not significant predictors (Table 4.20). An ANOVA was calculated between the three models to examine the R^2 increase between them. Model 1 accounted for 33% of the variance and Model 2 accounted for 36% of the variance ($R^2 = .03$), $F(1, 228) = 8.71, p < .01$, and was significant. Model 2 accounted for 36% of the variance and Model 3 accounted for 37% of the variance ($R^2 = .01$), $F(6, 222) = .79, p = .58$, and was not significant.

Another hierarchical analysis was conducted to examine the predictive validity of the individual differences on effort expectations. The purpose of this analysis was to examine individual differences predicting the effort expectancy attitude. Model 1 predicted effort expectancy with neuroticism, extraversion, and propensity to trust and was not significant $F(3, 227) = 2.54, p = .06, R^2 = .03$. Neuroticism ($t = -1.82, p = .07$), extraversion ($t =$

Table 4.20: Hierarchical Regression Predicting Performance Expectancy

Predictor Variable	Model 1			Model 2			Model 3		
	β	SE	t	β	SE	t	β	SE	t
Intercept	1.31	0.29	4.59	1.05	0.29	3.56	1.26	0.44	2.84
Effort Expectancy	0.64	0.06	10.63	0.62	0.06	10.48	0.66	0.07	9.93
Trust				0.09	0.03	2.95	0.09	0.03	2.68
Neuroticism NEO							0.01	0.04	0.33
Extraversion NEO							0.02	0.03	0.67
Verbal							-0.06	0.07	-0.86
Math							-0.02	0.04	-0.59
Spatial							-0.06	0.06	-0.96
Organizational							0.06	0.06	0.48

Note. Model 1 $F(1, 229) = 113, p < .001, R^2 = 0.33, R^2_{adj.} = 0.33$. Model 2 $F(2, 228) = 62.73, p < .001, R^2 = 0.36, R^2_{adj.} = 0.35$. Model 3 $F(8, 222) = 16.19, p < .001, R^2 = 0.37, R^2_{adj.} = 0.35$.

.84, $p = .40$), and propensity to trust ($t = .57, p = .57$) were not significant predictors in this model. Model 2 predicted effort expectancy with the prior personality traits, adding the self-concept variables and was significant $F(7, 223) = 8.36, p < .001, R^2 = .21$. In Model 2, organizational self-concept ($t = 3.65, p < .001$) was a significant predictor. Neuroticism ($t = .25, p = .80$), extraversion ($t = .11, p = .92$), propensity to trust ($t = .31, p = .76$), verbal self-concept ($t = 1.87, p = .06$), math self-concept ($t = 1.84, p = .07$), and spatial self-concept ($t = 1.49, p = .14$) were not significant predictors (Table 4.21). An ANOVA was conducted between Model 1 and Model 2 to determine how much variance in effort expectancy was explained by self-concept over and above the personality variables. Model 1 accounted for 3% of the variance in effort expectancy and Model 2 accounted for 21% of the variance in effort expectancy, significantly more than Model 1 ($\Delta R^2 = .15$), $F(4, 223) = 12.35, p < .001$.

Lastly, a hierarchical regression analysis was conducted predicting the social influence variable. Model 1 predicted social influence with the personality variables and was significant $F(3, 227) = 3.31, p = .02, R^2 = .04$. In this model, extraversion was a significant predictor ($t = 2.76, p < .01$), whereas neuroticism ($t = -.12, p = .91$) and propensity to trust ($t = -.20, p = .84$) were not significant predictors. Model 2 added the self-concept variables and was significant $F(7, 223) = 2.56, p = .01, R^2 = .07$. In Model 2, extraversion

Table 4.21: Hierarchical Regression Predicting Effort Expectancy

Predictor Variable	Model 1			Model 2		
	β	SE	t	β	SE	t
Intercept	4.71	0.23	20.82	2.38	0.42	5.71
Neuroticism NEO	-0.07	0.04	-1.82	0.01	0.04	0.25
Extraversion NEO	0.03	0.04	0.84	0.00	0.03	0.11
Trust	0.02	0.04	0.57	0.01	0.03	0.31
Verbal				0.12	0.07	1.87
Math				0.07	0.04	1.84
Spatial				0.09	0.06	1.49
Organizational				0.20	0.05	3.65

Note. Model 1 $F(3, 227) = 2.54, p = .06, R^2 = 0.03, R^2_{adj.} = 0.02$. Model 2 $F(7, 223) = 8.36, p < .001, R^2 = 0.21, R^2_{adj.} = 0.18$.

($t = 2.17, p = .03$) and organizational self-concept ($t = 2.44, p = .02$) were significant predictors while neuroticism ($t = .54, p = .59$), propensity to trust ($t = -.17, p = .87$), verbal self-concept ($t = .19, p = .85$), and math self-concept ($t = .73, p = .47$) were not significant predictor (Table 4.22). The ANOVA calculation that examined the variance increase between Model 1 and Model 2 was not significant ($\Delta R^2 = .03$), $F(4, 223) = 1.95, p = .10$.

Table 4.22: Hierarchical Regression Predicting Social Influence

Predictor Variable	Model 1			Model 2		
	β	SE	t	β	SE	t
Intercept	2.65	0.28	12.87	2.65	0.56	4.76
Neuroticism NEO	-0.01	0.05	-0.12	0.03	0.05	0.54
Extraversion NEO	0.13	0.05	2.76	0.10	0.05	2.17
Trust	-0.01	0.04	-0.20	-0.01	0.04	-0.17
Verbal				0.16	0.09	0.19
Math				0.04	0.05	0.73
Spatial				-0.03	0.08	-0.36
Organizational				0.18	0.07	2.44

Note. Model 1 $F(3, 227) = 3.31, p = .02, R^2 = 0.04, R^2_{adj.} = 0.03$. Model 2 $F(7, 223) = 2.56, p = .01, R^2 = 0.07, R^2_{adj.} = 0.05$.

4.4.3 Behavioral Intention Responses to Individual Vignettes

Further analyses were conducted to examine whether there were response differences between the individual vignette contexts by looking at descriptive statistics. The context with the highest behavioral intention score was using AI for navigation ($M = 5.08, SD = 1.01$), while the context with the lowest behavioral intention score was using AI to write a dating profile for you ($M = 2.99, SD = 1.60$). The mean behavioral intention scores for vignettes that fell toward negative intentions were writing a dating profile, resolving a disagreement with a colleague, matching with new friends based on personality, forming a group for a project, deciding between two job offers, and decorating a room. Those means that fell more toward positive intentions were navigation, adjusting cooking measurements, interpreting data, creating a monthly budget, breaking down goals into sub-tasks, and summarizing empirical research. When comparing the contexts with the highest intention scores and lowest intention scores a theme seemed to emerge such that the vignettes that received more negative intentions often involved a social aspect. Details regarding descriptive statistics of behavioral intention scores for each vignette can be found in Table 4.23, and bivariate correlations between vignettes can be found in Table 4.24. The themes that emerged were further analyzed with exploratory factor analysis (EFA).

A 2-factor EFA was conducted using the Quartimax orthogonal rotation method and principal axis factoring extraction. The Quartimax orthogonal rotation method was chosen to minimize the number of factors needed to explain the vignettes and identify a possible general factor and residual factor of behavioral intentions to use AI. Factor 1 (i.e., the general factor) consisted of all 20 vignettes and explained 39% of the variance with factor loadings ranging from .43 to .71. Factor 2 (i.e., the residual factor) consisted of 3 vignettes (MATH2, MATH3, NEUT1) and explained 5% of the variance with factor loadings ranging from .34 to .54. The rotated factor solution matrix is found in Table 4.25.

Table 4.23: Descriptive Statistics for Vignette BI Responses

Vignette ID	Brief Description	Mean	SD
EX1	Group formation for project	3.40	1.53
EX2	Matching with new friends	3.22	1.50
EX3	Writing a dating profile	2.99	1.60
NEU1	Prepare a sensitive speech	3.93	1.45
NEU2	Decide between choosing two jobs	3.42	1.47
NEU3	Resolving disagreement with colleague	3.03	1.55
VERB1	Writing email to miss a business day	3.95	1.57
VERB2	Writing a cover letter for a job	4.27	1.31
VERB3	Summarize empirical research	4.28	1.41
MATH1	Create a monthly budget	4.48	1.36
MATH2	Adjusting cooking measurements	4.70	1.28
MATH3	Data interpretation	4.52	1.18
SPAT1	Decorating a room	3.42	1.53
SPAT2	Constructing furniture	3.81	1.51
SPAT3	Design a flyer	4.16	1.32
ORG1	Organize and prioritize tasks	4.22	1.45
ORG2	Organize email folders	4.12	1.54
ORG3	Creating subtasks from a goal	4.36	1.34
NEUT1	Navigation	5.08	1.01
NEUT2	Recommend a television show	4.18	1.38

Factor 1: Interpersonal/Social Contexts

Factor 1 consisted primarily of contexts where the outcomes involve social outcomes such as writing a dating profile, forming a group for a project, deciding between two job offers, or resolving a disagreement with a colleague. In other words, the decision support being provided by the AI in these scenarios involved interpersonal outcomes.

Factor 2: Impersonal/Non-Social Contexts

Factor 2 contrasts with Factor 1 in that the use of AI in these vignettes did not involve an inherent or salient social element. Examples of vignettes associated with this factor include creating a monthly budget, generating an interpretation of a dataset, organizing email folders, or navigating to a destination.

Table 4.24: Correlation Table of Behavioral Intention Responses by Vignette

	E1	E2	E3	N1	N2	N3	V1	V2	V3	M1	M2	M3	S1	S2	S3	O1	O2	O3	NE1	NE2
EX1	1.00	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
EX2	0.44	1.00	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
EX3	0.47	0.47	1.00	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
NEU1	0.47	0.47	0.43	1.00	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
NEU2	0.64	0.45	0.37	0.46	1.00	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
NEU3	0.59	0.39	0.40	0.47	0.59	1.00	-	-	-	-	-	-	-	-	-	-	-	-	-	-
VERB1	0.47	0.46	0.57	0.55	0.44	0.44	1.00	-	-	-	-	-	-	-	-	-	-	-	-	-
VERB2	0.46	0.37	0.45	0.49	0.45	0.48	0.68	1.00	-	-	-	-	-	-	-	-	-	-	-	-
VERB3	0.53	0.41	0.39	0.60	0.45	0.43	0.49	0.51	1.00	-	-	-	-	-	-	-	-	-	-	-
MATH1	0.41	0.39	0.31	0.43	0.38	0.48	0.40	0.33	0.35	1.00	-	-	-	-	-	-	-	-	-	-
MATH2	0.31	0.25	0.18	0.30	0.29	0.30	0.28	0.34	0.41	0.42	1.00	-	-	-	-	-	-	-	-	-
MATH3	0.33	0.29	0.20	0.46	0.33	0.26	0.34	0.41	0.56	0.36	0.38	1.00	-	-	-	-	-	-	-	-
SPAT1	0.38	0.39	0.46	0.46	0.49	0.41	0.43	0.45	0.43	0.33	0.27	0.30	1.00	-	-	-	-	-	-	-
SPAT2	0.38	0.35	0.38	0.45	0.42	0.48	0.29	0.39	0.44	0.39	0.35	0.34	0.46	1.00	-	-	-	-	-	-
SPAT3	0.47	0.37	0.47	0.48	0.45	0.40	0.44	0.47	0.56	0.35	0.38	0.51	0.48	0.43	1.00	-	-	-	-	-
ORG1	0.46	0.33	0.38	0.40	0.46	0.43	0.51	0.46	0.33	0.54	0.31	0.31	0.39	0.35	0.34	1.00	-	-	-	-
ORG2	0.34	0.33	0.27	0.37	0.36	0.33	0.30	0.32	0.36	0.41	0.37	0.37	0.40	0.40	0.40	0.48	1.00	-	-	-
ORG3	0.37	0.34	0.30	0.43	0.37	0.40	0.42	0.45	0.35	0.47	0.40	0.31	0.36	0.38	0.37	0.70	0.42	1.00	-	-
NEUT1	0.17	0.19	0.20	0.29	0.27	0.12	0.27	0.30	0.39	0.34	0.51	0.38	0.29	0.27	0.40	0.35	0.28	0.40	1.00	-
NEUT2	0.33	0.31	0.20	0.29	0.36	0.29	0.27	0.34	0.31	0.43	0.29	0.43	0.28	0.32	0.32	0.30	0.30	0.22	0.33	1.00

Note. All bolded values are significant at the $p < .05$ level. All bolded and underlined values are significant at the $p < .01$ level. The UTAUT variables are the aggregated average of responses to all vignettes except the high and low liability conditions. $df = 229$.

Table 4.25: 2-Factor EFA with Quartimax Orthogonal Rotation

Vignette ID	Brief Description	Factors	
		1	2
EX1	Group formation for project	0.71	-0.17
EX2	Matching with new friends	0.61	-0.10
EX3	Writing a dating profile	0.63	-0.24
NEU1	Prepare a sensitive speech	0.71	0.00
NEU2	Decide between choosing two jobs	0.70	-0.10
NEU3	Resolving disagreement with colleague	0.69	-0.17
VERB1	Writing email to miss a business day	0.71	-0.13
VERB2	Writing a cover letter for a job	0.70	-0.02
VERB3	Summarize empirical research	0.69	0.13
MATH1	Create a monthly budget	0.61	0.21
MATH2	Adjusting cooking measurements	0.48	0.46
MATH3	Data interpretation	0.54	0.34
SPAT1	Decorating a room	0.64	-0.02
SPAT2	Constructing furniture	0.60	0.09
SPAT3	Design a flyer	0.67	0.13
ORG1	Organize and prioritize tasks	0.65	0.13
ORG2	Organize email folders	0.55	0.23
ORG3	Creating subtasks from a goal	0.61	0.22
NEUT1	Navigation	0.43	0.54
NEUT2	Recommend a television show	0.47	0.23

Note. Factor loadings greater than .30 are highlighted.

Cross-Factor Loadings

The factor scores for 3 vignettes loaded on both factors including summarizing empirical research, designing a flyer, and prioritizing tasks. It may be that these contexts did not explicitly or clearly indicate a social consequence but were contexts that participants could imagine having social interpersonal aspects. For example, summarizing empirical research for personal consumption or for work-related tasks.

From here, three composite variables were created: (1) a general composite consisting of all vignettes; (2) an impersonal/non-social composite consisting of 11 vignettes (VERB3, MATH1, MATH2, MATH3, SPAT2, SPAT3, ORG1, ORG2, ORG3, NEUT1, NEUT2); and (3) an interpersonal/social context composite consisting of 6 vignettes (EX1, EX2, EX3, NEU2, NEU3, VERB1) as presented in Table 4.26. Three vignettes (NEU1,

Table 4.26: Vignettes Grouped by Identified Composite Factors

Vignette ID	Brief Description
Interpersonal Composite	
EX1	Group formation for project
EX2	Matching with new friends
EX3	Writing a dating profile
NEU2	Decide between choosing two jobs
NEU3	Resolving disagreement with colleague
VERB1	Writing email to miss a business day
Impersonal Composite	
VERB3	Summarize empirical research
MATH1	Create a monthly budget
MATH2	Adjusting cooking measurements
MATH3	Data interpretation
SPAT2	Constructing furniture
SPAT3	Design a flyer
ORG1	Organize and prioritize tasks
ORG2	Organize email folders
ORG3	Creating subtasks from a goal
NEUT1	Navigation
NEUT2	Recommend a television show

VERB2, and SPAT1) were omitted because they did not load substantially positively or negatively on the second factor in the Quartimax rotated factor matrix. These composites were computed by transforming the behavioral intention responses to each vignette into z-scores and sum aggregating them among their respective composites. Correlations between the composites and predictor variables are found in Table 4.27.

Table 4.27: Bivariate Correlations of Predictor Variables and Behavioral Intention Composite Variables

	N NEO	E NEO	E MPQ	SP	SC	Trust	O SC	V SC	MSC	S SC	OR SC	G	Imp	Inter
Neuroticism NEO	1.00	-	-	-	-	-	-	-	-	-	-	-	-	-
Extraversion NEO	-0.37	1.00	-	-	-	-	-	-	-	-	-	-	-	-
Extraversion MPQ	-0.26	0.61	1.00	-	-	-	-	-	-	-	-	-	-	-
Social Potency MPQ	-0.25	0.37	0.73	1.00	-	-	-	-	-	-	-	-	-	-
Social Closeness MPQ	-0.14	0.71	0.67	0.33	1.00	-	-	-	-	-	-	-	-	-
Trust	-0.21	0.41	0.29	0.15	0.41	1.00	-	-	-	-	-	-	-	-
Overall SC	-0.32	0.24	0.15	0.12	0.14	0.07	1.00	-	-	-	-	-	-	-
Verbal SC	-0.19	0.16	0.05	0.02	0.07	0.13	0.58	1.00	-	-	-	-	-	-
Math SC	-0.20	0.11	0.18	0.22	0.03	0.13	0.22	0.21	1.00	-	-	-	-	-
Spatial SC	-0.33	0.10	0.16	0.21	0.04	0.12	0.43	0.40	0.53	1.00	-	-	-	-
Organizational SC	-0.32	0.29	0.23	0.19	0.17	0.10	0.75	0.33	0.21	0.43	1.00	-	-	-
General Comp BI	-0.05	0.18	0.13	0.15	0.09	0.17	0.18	0.08	0.13	0.14	0.25	1.00	-	-
Impersonal Comp BI	-0.06	0.18	0.14	0.16	0.10	0.17	0.25	0.17	0.13	0.18	0.29	0.94	1.00	-
Interpersonal Comp BI	-0.01	0.16	0.08	0.12	0.06	0.14	0.04	-0.06	0.08	0.06	0.13	0.88	0.70	1.00

Note. All bolded values are significant at the $p < .05$ level. All bolded and underlined values are significant at the $p < .01$ level. Overall SC is the mean aggregate of all ability self-concept questions. $df = 229$.

CHAPTER 5

DISCUSSION

The present vignette study sought to better predict the circumstances in which individuals might choose to adopt (or not adopt) an AI tool to assist them in various domains by incorporating select personality traits and ability self-concepts to the UTAUT framework. This research was guided by literature that indicated cases of mixed perceptions toward the use of AI tools and intended to take an individual differences approach to understanding these disparate views. The following section will first discuss the hypothesized findings as well as additional supplementary findings of interest. Then, study limitations, theoretical and practical implications, and future directions will be presented before concluding.

5.1 Interpretation of Results

5.1.1 Individual Differences and Adoption Intentions

The first guiding research question concerned how much individual differences in select personality traits and ability self-concepts influenced people's intentions to adopt AI in general. Independently, the personality traits (i.e., extraversion, neuroticism, and propensity to trust) explained 5% of the variance in behavioral intentions to use AI, while ability self-concept (i.e., math, verbal, spatial, and organizational) accounted for a combined 7% of the variance in overall intentions to use AI. However, when examining the incremental validity of these variables in predicting behavioral intentions to use AI over and above the UTAUT constructs, they did not add further significant predictive variance. These results indicate that practically, UTAUT seems generally adequate in predicting people's intentions to use AI and that the individual difference variables are not accounting for meaningful variance in whether people think they would use an AI tool in the future.

The second guiding research question concerned predicting intentions to use AI within various contexts and whether personality and self-concept might improve the situational prediction of UTAUT. Across various situations, UTAUT was found to independently predict over 80% of the variance in use intentions indicating support for UTAUT's predictive validity across situations. Some notable limitations may be influencing these results that are further detailed in the limitations section regarding power and possible range restrictions. Given these results of the hypotheses, the next step was to examine whether and how personality and self-concept might influence the attitudes about AI as captured by UTAUT.

5.1.2 Personality and Attitudes

Further analyses were conducted to examine which of the UTAUT attitudes the personality and self-concept variables are most likely to influence. This section addresses the significant findings of the personality variables on UTAUT's attitude constructs. NEO extraversion was found to be a significant, but not practically related predictor of social influence ($R^2 = .04$) when controlling for the other personality and self-concept variables. Further analyses were conducted recreating this hierarchical regression by swapping NEO extraversion with Tellegen's MPQ extraversion facets to better illustrate whether facets of extraversion drive these attitudes. In this analysis social potency was a significant predictor whereas social closeness was not. This suggests that those who are more socially forceful and decisive may perceive their use of technology to be more important to relevant others.

Most often in human factors psychology trust is incorporated in terms of the level of trustworthiness that a subject perceives in an automated agent. This study found that propensity to trust, a more stable and distal trait than perceived trustworthiness, contributed about 3% additional variance in predicting AI performance expectations over and above effort expectations. In other words, individuals who tend to be trusting toward others in general may be slightly more likely to hold higher initial expectations about an AI's ability to perform tasks. The scale used to measure propensity to trust uses human-human inter-

actions as the anchor for its questions and was intentionally applied to predicting human-machine interaction outcomes. While highlighting the importance of understanding differences in human-machine interactions, these findings further suggest that one's tendency to trust humans may generalize to attitudes about how AI will perform prior to its use. Finally, neuroticism was not found to significantly predict any of the UTAUT variables indicating that neuroticism is likely not meaningfully related to understanding these aspects of AI attitudes and adoption within the bounds of this study.

5.1.3 Self-Concept and Attitudes

The ability self-concept variables were expected to have a negative relationship with behavioral intentions and attitude variables, such that higher self-concept would result in individuals being less likely to use AI tools in the future. It was predicted that people who view themselves as capable in various domains might consider using AI to assist them in such domains as more of a hindrance, whereas those lower in self-concept might rely on AI to make up for a perceived deficit in abilities. The results, however, indicated that the opposite relationship was true. Ability self-concept facets had small positive correlations with all the UTAUT variables but correlated most notably with effort expectancy ($r = .27 - .37$). This could be interpreted in a few ways. It may be that higher ability self-concept is associated with confidence in one's ability to identify AI output errors related to task domains. The tendency for AI to err has become well understood and expected by the general population such that ChatGPT for example clearly states, "ChatGPT can make mistakes. Consider checking important information." (OpenAI, 2023). If monitoring AI errors in domain tasks is of concern to the user their level of perceived effort required to use the agent may be reduced for those with higher ability self-concept. On the other hand, as detailed later in the limitations section, the range of self-concept scores within the sample was restricted, with most participants on the higher end of these measures which may not have accounted for those who perceive low ability self-concept.

Organizational self-concept was found to predict a significant amount of variance in overall effort expectancy. Perhaps individuals who perceive themselves as effective organizers also view AI as a tool to enhance their ability to organize, rather than detract from it. While personality and self-concept had varied relationships with attitudes and intentions toward using AI, perceptions of liability clearly influenced all these outcome variables.

5.1.4 Situational Influence of Perceived Liability

Exposure to the high or low liability group resulted in significantly different attitudes and intentions toward using AI, such that those in the high liability group had significantly lower attitude and intention scores compared to the low liability group. This finding emphasizes the situational nuance that influences people's attitudes and intentions to use AI. Other researchers have explored the concept of perceived risk as it relates to AI use. For example, Stuck & Walker (2020) differentiated perceived relational risk and situational risk as it relates to trust and risk-taking behaviors in human-automation interactions. The subject of risk in this study is related to whether responsibility for the consequences of an AI error is on the user or an entity external to the individual such as a manufacturer or organization. The finding that perceptions of liability influence individuals' attitudes prior to interaction is of particular interest. Perhaps general attitudes about AI such as expectations of performance and effort are also influenced by information about the situation and consequences rather than capabilities of the AI itself.

5.1.5 Individual Vignette Characteristics and Behavioral Intentions

The results of the EFA evidenced differences in response patterns between AI use contexts that were impersonal compared to those that involved interpersonal outcomes. While small, the differences in correlations between the self-concept variables and the composites are worth noting. The ability self-concept had slightly larger correlations with the impersonal behavioral intention composite ($r = .13 - .29$) compared to the interpersonal behavioral

intention composite ($r = -.06 - .13$). The differences in these correlations might suggest that different individual difference variables become relevant predictors depending on characteristics of the situation. In other words, certain traits might be differentially important when predicting behavioral intentions to use AI depending on salient contextual components.

5.1.6 Limitations

Several limitations in this study that notably affect results and interpretations of the data are presented in this section. The first limitation concerns the situational vignettes that were created and used for participants to anchor their UTAUT responses too. Post-hoc correlational analyses evidenced that the vignettes were not activating their matched traits as intended. I expected that behavioral intention scores on the vignettes would correlate in the same direction with their matched traits and more strongly than the non-matched traits, however, this was not the case. For example, some vignette groups (i.e., neuroticism, verbal ability, and math ability) had vignettes that correlated in different directions. This may also be the result of a limitation of the sample, as there were possible range restrictions among the ability self-concept variables. Responses to the self-concept variables were negatively skewed, such that there is less representation of individuals who scored low in ability self-concept in this sample. Furthermore, the vignettes were not systematically validated prior to conducting the study which is also a likely influence on the trait-matched vignettes not activating as anticipated.

Next, post hoc power analyses indicated that adequate power was not achieved for the hypotheses that tested the incremental predictive validity of the personality and self-concept variables over and above the core UTAUT constructs. These analyses revealed that the hypothesized effect sizes of personality and self-concept in the hierarchical models were overestimated and that the achieved sample was not adequate for detecting the desired effects. Unfortunately, collecting additional data to increase the sample size was not

feasible due to the lack of additional funding for further Prolific recruitment. While more participants could have been collected among an undergraduate sample via SONA it would have been inappropriate to analyze their responses along with the Prolific sample. Given this, the hypotheses for hierarchical regressions should be interpreted with caution.

Additionally, the present study did not examine or measure actual AI use behavior and instead relied on behavioral intention responses to vignettes about using AI. It should be emphasized that people's attitudes and intentions do not always coincide with expected behaviors. As for the variables, only extraversion, neuroticism, and propensity to trust were selected as relevant personality traits. While extraversion and neuroticism represent personality at a broad level, Tellegen's MPQ was employed to explore the sub-facets of extraversion. When entered into the hierarchical regressions, the influence of the personality variables were examined at the aggregate level. While personality variable choices were informed by prior research, the overall personality aggregate employed does not represent all aspects of personality. In other words, it may be that other aspects of personality not captured in this study may have accounted for additional variance that the personality traits examined here did not.

5.1.7 Theoretical Implications

Theoretically, the degree to which individual differences in personality traits and self-evaluations play a role in predicting technology adoption behavior, in general, has been an open question. While the influence of personality traits has been explored (Siebert et al., 2021) researchers continue to promote the importance of understanding the impact of individual differences as the evidence is still inconclusive (e.g., V. Venkatesh, 2022). The inconclusiveness is, in part, likely due to a departure of the field from general theoretical extension in favor of applied work focused on using acceptance modeling to predict the use of specific technologies in specific contexts. This study assisted in closing this gap by implementing a vignette research methodology to examine responses to a variety of AI use

contexts. With AI use cases continuing to widen, it is necessary for theoretical models of AI adoption and acceptance to account for this.

Additionally, when it comes to understanding the impact of self-evaluations, most studies tend to include computer self-efficacy (e.g., Chiu & Wang, 2008; Liu et al., 2022; V. Venkatesh & Davis, 1996) rather than ability self-concept for broader domains. Since many embedded AI applications are leaning toward augmenting various knowledge tasks (Tschang & Almirall, 2021) and skills, this study offered a more generalizable approach to understanding the individual differences that may influence adoption of AI as task augmenting technologies. This approach could be applied to other technology domains as well. While this study is still narrow by focusing on the technology domain of AI, the field may benefit from looking at technologies that can be similarly categorized to improve the overall generalizability of the results. In general, this research also seeks to provide additional information regarding where personality and self-concept variables should be placed within the nomological network of technology acceptance.

5.1.8 Practical Applications

This study highlights the practical applications of the UTAUT model as well. First, I intended to re-emphasize the utility of technology acceptance modeling, not only for understanding attitudes toward specific technologies but for technologies that are still under development or purely conceptual. For example, user experience (UX) designers and researchers are often constrained by fast-paced deadlines that often require conceptual user testing prior to or during product development. The UTAUT offers a relatively quick and valid methodology for UX researchers and designers to evaluate both attitudes and overall adoption intentions. The vignette methodology used in this study also enables researchers the flexibility to measure participants' attitudes towards a variety of design characteristics needless of a completed product. This idea stays true to the concept of "acceptance testing" that Davis presented when he first proposed the TAM in 1986 and hopefully encourages re-

searchers and practitioners to expand upon it.

This research may also be of benefit to managers by providing them with a better understanding of the influential variables leading employees to be more likely to adopt new work-augmenting AI technologies. For example, it might take more effort for employees with lower perceptions of their abilities to see the benefit that an AI could add to assisting them in a domain compared to those who perceive higher ability self-concept. Additionally, by considering the impact of individual differences, designers might better prepare and communicate the use of innovative AI technologies to meet the needs of a range of users. New and robust applications of AI are here to stay and will continue to grow, and the present study helps inform the usefulness of individual differences traits in predicting AI tools in preparation for practical applications to continue expanding.

5.1.9 Future Directions

Given the results of this present study, there are a few recommendations for future research being undertaken in this area. First, this study, like many others examining technology attitudes and adoption, relied on assessing behavioral intentions to use technology for methodological simplicity and practicality. It is important that researchers also explore the link between behavioral intentions and actual use behavior as there still lies an empirical gap here for many technology acceptance studies. While conducting research on undeveloped technology, the Wizard of Oz methodology is one suggestion for researchers to use for conducting more ecologically valid studies that might also measure actual use behavior. Attention should also be directed toward mediators or moderators linking intentions and actual use. This is an ongoing theoretical gap that is present in UTAUT and other technology acceptance models. I also omitted the UTAUT facilitating conditions variable from this study due to its scope being focused on the influence of the individual difference variables rather than external entities. Future research might consider how these variables interact with perceived facilitating conditions within the workplace. For example, employ-

ees with lower self-efficacy for technology use may perceive facilitating conditions for a new technology implementation differently than those who feel more capable of using new technologies.

Future research might also be conducted regarding the situational impact of various perceptions of risk on AI adoptions such as relational and situational risk as theoretically modeled in Stuck and colleagues' 2022 paper. While the present findings suggest that personality and ability self-concept variables do not seem meaningfully influential in predicting behavioral intentions to adopt AI over and above effort and performance expectancy, individuals with certain traits or self-perceptions may differ in how they perceive potential risk involved with using AI in different situations. In the future, researchers might use such a framework of perceived risk to construct human-AI interaction situations varied on contexts of perceived relational or situational risk. Furthermore, this study used the midpoint of Parasuraman's (2000) levels of automation where AI presents and executes operations at the user's discretion. Future studies might also vary AI use contexts at different levels of automation.

Finally, when exploring the influence of personality traits on technology use variables, attention should be directed toward their influence on attitude development rather than their direct influence on behavioral intentions. In doing so, researchers should also incorporate more targeted personality trait sub-facets to improve the interpretability of results, rather than relying on broader personality traits.

5.1.10 Conclusion

I sought to better understand the influence that personality and ability self-concept have on attitudes and intentions to adopt AI when incorporated into the Unified Theory of Acceptance and Use of Technology. It employed a vignette methodology to examine reactions to a variety of AI use contexts to improve the generalizability of results. This vignette methodology allows for a more robust use of technology acceptance models particularly

when parsing out various situational differences between different uses of AI.

I found that UTAUT's core variables, performance expectancy, effort expectancy, and social influence explain about 87% of the variance in behavioral intentions to use AI when aggregated across all scenarios, and that independently, personality traits (extraversion, neuroticism, trust propensity) explain 5% of the variance in behavioral intentions to use AI, while ability self-concept (math, verbal, spatial, organizational) account for 7%. However, when entered into a hierarchical regression, the individual difference variables do not explain meaningful additional variance indicating that the UTAUT attitudes seem adequate in predicting whether people intend to adopt AI across situations.

Based on the results from this study, I suggest that personality traits and ability self-concept may be best analyzed as distal predictors of behavioral intentions, accounting for more variance in the attitude variables in the UTAUT model. Individuals who are more extraverted, particularly those who are more socially forceful and decisive may have stronger perceptions regarding whether using technology is important to those around them. Interestingly, and more notably, the results suggest that those who have a higher propensity to trust others are more likely to have positive preconceived attitudes about AI's ability to perform. As for ability self-concept, those who have higher self-concept in academic domains are more likely to perceive AI as less effortful to use, perhaps due to confidence in one's ability to identify and resolve potential AI errors. Furthermore, people's attitudes and intentions to use AI seem to be driven by salient situational components such as personal liability, risk, or interpersonal consequences that might be involved. Previous research incorporating individual difference variables are often only applied to understanding technology attitudes and adoption in single contexts. The present study intended to respond the Venkatesh's (2022) call for research around the application of UTAUT to understanding individual and environmental influences on attitude development and adoption of AI technologies to augment tasks. With continued advancements and uses of ChatGPT and other natural language models, it is important to take a person-centric approach toward under-

standing our differed relationships with technology so it may be better implemented and designed with the individual in mind.

REFERENCES

- Abbey, J. D., & Meloy, M. G. (2017). Attention by design: Using attention checks to detect inattentive respondents and improve data quality. *Journal of Operations Management*, 53-56(1), 63–70. <https://doi.org/10.1016/j.jom.2017.06.001>
- Ackerman, P. L. (1996). A theory of adult intellectual development: Process, personality, interests, and knowledge. *Intelligence*, 22(2), 227–257. [https://doi.org/10.1016/S0160-2896\(96\)90016-1](https://doi.org/10.1016/S0160-2896(96)90016-1)
- Ackerman, P. L., Bowen, K. R., Beier, M. E., & Kanfer, R. (2001). Determinants of individual differences and gender differences in knowledge. *Journal of Educational Psychology*, 93(4), 797–825. <https://doi.org/10.1037/0022-0663.93.4.797>
- Ackerman, P. L., & Heggestad, E. D. (1997). Intelligence, personality, and interests: Evidence for overlapping traits. *Psychological Bulletin*, 121(2), 219–245. <https://doi.org/10.1037/0033-2909.121.2.219>
- Ackerman, P. L., & Wolman, S. D. (2007). Determinants and validity of self-estimates of abilities and self-concept measures. *Journal of Experimental Psychology: Applied*, 13(2), 57–78. <https://doi.org/10.1037/1076-898X.13.2.57>
- Aggarwal, C. C. (2016). *Recommender systems: The textbook*. Springer.
- Ajzen, I. (1998). Models of human social behavior and their application to health psychology. *Psychology & Health*, 13(4), 735–739. <https://doi.org/10.1080/08870449808407426>
- Ajzen, I. (2005). *Attitudes, personality, and behaviour*. McGraw-Hill Education.
- Alarcon, G. M., Lyons, J. B., Christensen, J. C., Bowers, M. A., Klosterman, S. L., & Capiola, A. (2018). The role of propensity to trust and the five factor model across the trust process. *Journal of Research in Personality*, 75, 69–82. <https://doi.org/10.1016/j.jrp.2018.05.006>
- Allport, G. W. (1937). *Personality: A psychological interpretation*. Holt.
- Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. *Psychological Review*, 84(2), 191–215. <https://doi.org/https://doi.org/10.1037/0033-295x.84.2.191>
- Barnett, T., Pearson, A. W., Pearson, R., & Kellermanns, F. W. (2015). Five-factor model personality traits as predictors of perceived and actual usage of technology. *European Journal of Information Systems*, 24(4), 374–390. <https://doi.org/10.1057/ejis.2014.10>

- Barrick, M. R., & Mount, M. K. (1991). The Big Five personality dimensions and job performance: A meta-analysis. *Personnel Psychology*, *44*(1), 1–26. <https://doi.org/10.1111/j.1744-6570.1991.tb00688.x>
- Barrick, M. R., Mount, M. K., & Judge, T. A. (2001). Personality and performance at the beginning of the new millennium: What do we know and where do we go next? *International Journal of Selection and Assessment*, *9*(1-2), 9–30. <https://doi.org/10.1111/1468-2389.00160>
- Benbya, H., Davenport, T. H., & Pachidi, S. (2020). Artificial intelligence in organizations: Current state and future opportunities. *SSRN Electronic Journal*, *19*. <https://doi.org/10.2139/ssrn.3741983>
- Bernerth, J. B., Aguinis, H., & Taylor, E. C. (2021). Detecting false identities: A solution to improve web-based surveys and research on leadership and health/well-being. *Journal of Occupational Health Psychology*, *26*(6), 564–581. <https://doi.org/10.1037/ocp0000281>
- Bong, M. (1999). Personal factors affecting the generality of academic self-efficacy judgments: Gender, ethnicity, and relative expertise. *The Journal of Experimental Education*, *67*(4), 315–331. <https://doi.org/10.1080/00220979909598486>
- Bong, M., & Skaalvik, E. M. (2002). Academic self-concept and self-efficacy: How different are they really? *Educational Psychology Review*, *15*. <https://link.springer.com/article/10.1023/A:1021302408382>
- Boontarig, W. (2016). Effect of personality factors on attitude towards the adoption of health information via online social networking. *2016 International Computer Science and Engineering Conference (ICSEC)*, 1–6. <https://doi.org/10.1109/ICSEC.2016.7859897>
- Carpenter, R. (2019). The future of artificial intelligence is job augmentation, not elimination. AiThORITY. <https://aithority.com/guest-authors/the-future-of-artificial-intelligence-is-job-augmentation-not-elimination/>
- Chao, C.-M. (2019). Factors determining the behavioral intention to use mobile learning: An application and extension of the UTAUT model. *Frontiers in Psychology*, *10*, 1652. <https://doi.org/10.3389/fpsyg.2019.01652>
- Chen, L., Chen, P., & Lin, Z. (2020). Artificial intelligence in education: A review. *IEEE Access*, *8*, 75264–75278. <https://doi.org/10.1109/ACCESS.2020.2988510>
- Chiu, C.-M., & Wang, E. T. (2008). Understanding Web-based learning continuance intention: The role of subjective task value. *Information & Management*, *45*(3), 194–201. <https://doi.org/10.1016/j.im.2008.02.003>

- Church, A. T. (1994). Relating the Tellegen and five-factor models of personality structure. *Journal of Personality and Social Psychology*, 67(5), 898–909. <https://doi.org/10.1037/0022-3514.67.5.898>
- Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed). L. Erlbaum Associates.
- Costa, P. T., & McCrae, R. R. (2008). The revised NEO personality inventory (NEO-PI-R). In *The SAGE Handbook of Personality Theory and Assessment: Volume 2 Personality Measurement and Testing* (pp. 179–198, Vol. 2). Sage Publications, Inc. <https://doi.org/10.4135/9781849200479.n9>
- Cuzzolin, F., Morelli, A., Cîrstea, B., & Sahakian, B. J. (2020). Knowing me, knowing you: Theory of mind in AI. *Psychological Medicine*, 50(7), 1057–1061. <https://doi.org/10.1017/S0033291720000835>
- Dastin, J. (2018). Amazon scraps secret AI recruiting tool that showed bias against women. <https://www.reuters.com/article/us-amazon-com-jobs-automation-insight/amazon-scraps-secret-ai-recruiting-tool-that-showed-bias-against-women-idUSKCN1MK08G>
- Davis, F. (1986). *A technology acceptance model for empirically testing new end-user information systems: Theory and Results* [Doctoral dissertation, Massachusetts Institute of Technology]. <http://hdl.handle.net/1721.1/15192>
- Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, 13(3), 319. <https://doi.org/10.2307/249008>
- Devaraj, S., Easley, R. F., & Crant, J. M. (2008). How Does Personality Matter? Relating the Five-Factor Model to Technology Acceptance and Use. *Information Systems Research*, 19(1), 93–105. <https://doi.org/10.1287/isre.1070.0153>
- Dietvorst, B. J., Simmons, J. P., & Massey, C. (2014). Algorithm aversion: People erroneously avoid algorithms after seeing them err. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.2466040>
- Digman, J. M. (1990). Personality structure: Emergence of the five-factor model. *Annual Review of Psychology*, 41(1), 417–440. <https://doi.org/10.1146/annurev.ps.41.020190.002221>
- Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, 39(2), 175–191. <https://doi.org/10.3758/BF03193146>

- Frazier, M. L., Johnson, P. D., & Fainshmidt, S. (2013). Development and validation of a propensity to trust scale. *Journal of Trust Research*, 3(2), 76–97. <https://doi.org/10.1080/21515581.2013.820026>
- Freund, P. A., & Kasten, N. (2012). How smart do you think you are? A meta-analysis on the validity of self-estimates of cognitive ability. *Psychological Bulletin*, 138(2), 296–321. <https://doi.org/10.1037/a0026556>
- Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. *Academy of Management Annals*, 14(2), 627–660. <https://doi.org/10.5465/annals.2018.0057>
- Goff, M. (1994). *Understanding vocational self-concept and related domains: A hierarchical factor-analytic approach*. [Doctoral dissertation, University of Minnesota].
- Goldberg, L. R. (1981). Language and individual differences: The search for universals in personality lexicons. In *Review of Personality and Social Psychology* (pp. 141–165). Sage Publication.
- Goldberg, L. R. (1999). A broad-bandwidth, public domain, personality inventory measuring the lower-level facets of several five-factor models. In *Personality psychology in Europe* (pp. 7–28, Vol. 7). Tillburg University Press.
- Goldberg, L. R., Johnson, J. A., Eber, H. W., Hogan, R., Ashton, M. C., Cloninger, C. R., & Gough, H. G. (2006). The international personality item pool and the future of public-domain personality measures. *Journal of Research in Personality*, 40(1), 84–96. <https://doi.org/10.1016/j.jrp.2005.08.007>
- Highhouse, S. (2008). Stubborn reliance on intuition and subjectivity in employee selection. *Industrial and Organizational Psychology*, 1(3), 333–342. <https://doi.org/10.1111/j.1754-9434.2008.00058.x>
- Hoff, K. A., & Bashir, M. (2015). Trust in automation: Integrating empirical evidence on factors that influence trust. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 57(3), 407–434. <https://doi.org/10.1177/0018720814547570>
- Jackson, L. A., von Eye, A., Fitzgerald, H. E., Zhao, Y., & Witt, E. A. (2010). Self-concept, self-esteem, gender, race and information technology use. *Computers in Human Behavior*, 26(3), 323–328. <https://doi.org/10.1016/j.chb.2009.11.001>
- John, O. P., & Srivastava, S. (1999). The Big Five Trait taxonomy: History, measurement, and theoretical perspectives. In *Handbook of personality: Theory and research* (pp. 102–138). Guilford Press.

- Jussupow, E., Benbasat, I., & Heinzl, A. (2020). Why are we averse toward algorithms? A comprehensive literature review on algorithm aversion. *Twenty-Eighth European Conference on Information Systems (ECIS2020) – A Virtual AIS Conference.*, 18. https://aisel.aisnet.org/ecis2020_rp/168
- Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons*, 62(1), 15–25. <https://doi.org/10.1016/j.bushor.2018.08.004>
- King, W. R., & He, J. (2006). A meta-analysis of the technology acceptance model. *Information & Management*, 43(6), 740–755. <https://doi.org/10.1016/j.im.2006.05.003>
- Kwak, Y., Seo, Y. H., & Ahn, J.-W. (2022). Nursing students' intent to use AI-based health-care technology: Path analysis using the unified theory of acceptance and use of technology. *Nurse Education Today*, 119, 105541. <https://doi.org/10.1016/j.nedt.2022.105541>
- Langer, M., & Landers, R. N. (2021). The future of artificial intelligence at work: A review on effects of decision automation and augmentation on workers targeted by algorithms and third-party observers. *Computers in Human Behavior*, 123, 106878. <https://doi.org/10.1016/j.chb.2021.106878>
- Lee, J. D., & See, K. A. (2004). Trust in Automation: Designing for Appropriate Reliance. *Human Factors*, 31.
- Liu, X., He, X., Wang, M., & Shen, H. (2022). What influences patients' continuance intention to use AI-powered service robots at hospitals? The role of individual characteristics. *Technology in Society*, 70. <https://doi.org/10.1016/j.techsoc.2022.101996>
- Loehlin, J. C. (1992). *Genes and environment in personality development*. Sage Publications, Inc.
- Logg, J. M., Minson, J. A., & Moore, D. A. (2019). Algorithm appreciation: People prefer algorithmic to human judgment. *Organizational Behavior and Human Decision Processes*, 151, 90–103. <https://doi.org/10.1016/j.obhdp.2018.12.005>
- Marangunić, N., & Granić, A. (2015). Technology acceptance model: A literature review from 1986 to 2013. *Universal Access in the Information Society*, 14(1), 81–95. <https://doi.org/10.1007/s10209-014-0348-1>
- Marsh, H. W. (2006). Significance of self-concept. *Vernon Wall Lecture*, 1(25), 5–7. <https://doi.org/10.53841/bpsvern.2006.1.25.5>

- Marsh, H. W. (1990). A multidimensional, hierarchical model of self-concept: Theoretical and empirical justification. *Educational Psychology Review*, 2(2), 77–172. <https://doi.org/10.1007/BF01322177>
- Marsh, H. W., Byrne, B. M., & Shavelson, R. J. (1988). A multifaceted academic self-concept: Its hierarchical structure and its relation to academic achievement. *Journal of Educational Psychology*, 80(3), 366–380. <https://doi.org/10.1037/0022-0663.80.3.366>
- Marsh, H. W., & Shavelson, R. (1985). Self-Concept: Its Multifaceted, Hierarchical Structure. *Educational Psychologist*, 20(3), 107–123. https://doi.org/10.1207/s15326985ep2003_1
- Matthews, G., Hancock, P. A., Lin, J., Panganiban, A. R., Reinerman-Jones, L. E., Szalma, J. L., & Wohleber, R. W. (2021). Evolution and revolution: Personality research for the coming world of robots, artificial intelligence, and autonomous systems. *Personality and Individual Differences*, 169, 109969. <https://doi.org/10.1016/j.paid.2020.109969>
- Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An Integrative Model of Organizational Trust. *The Academy of Management Review*, 20(3), 709. <https://doi.org/10.2307/258792>
- McCarthy, J., Minsky, M. L., Rochester, N., Corporation, I. B. M., & Shannon, C. E. (1955). A proposal for the Dartmouth summer research project on artificial intelligence. <http://www.formal.stanford.edu/jmc/history/dartmouth/dartmouth.html>
- Meehl, P. E. (1954). *Clinical versus statistical prediction: A theoretical analysis and a review of the evidence*. University of Minnesota Press. <http://dx.doi.org/10.1037/11281-000>
- OpenAI. (2023). ChatGPT: Optimizing language models for dialogue. <https://openai.com/blog/chatgpt/>
- Özbek, V., Alnıaçık, Ü., Koc, F., Akkılıç, M. E., & Kaş, E. (2014). The impact of personality on technology acceptance: A study on smart phone users. *Procedia - Social and Behavioral Sciences*, 150, 541–551. <https://doi.org/10.1016/j.sbspro.2014.09.073>
- Parasuraman, R., Sheridan, T. B., & Wickens, C. D. (2000). A model for types and levels of human interaction with automation. *IEEE Transactions on Systems, Man, and Cybernetics – Part A: Systems and Humans*, 30(3), 286–297. <https://doi.org/10.1109/3468.844354>

- Park, J., & Woo, S. E. (2022). Who Likes Artificial Intelligence? Personality Predictors of Attitudes toward Artificial Intelligence. *The Journal of Psychology*, *156*(1), 68–94. <https://doi.org/10.1080/00223980.2021.2012109>
- Reisenzein, R., Hildebrandt, A., & Weber, H. (2020). Personality and emotion. In *The Cambridge handbook of personality psychology* (pp. 81–99). Cambridge University Press. <https://doi.org/10.1017/9781108264822.009>
- Rosenberg, M. (1965). *Society and the adolescent self-image*. Princeton University Press.
- Rotter, J. B. (1971). Generalized expectancies for interpersonal trust. *American Psychologist*, *26*(5), 443–452. <https://doi.org/10.1037/h0031464>
- Rudin, C., & Radin, J. (2019). Why Are We Using Black Box Models in AI When We Don't Need To? A Lesson From An Explainable AI Competition. *Harvard Data Science Review*, *1*(2). <https://doi.org/10.1162/99608f92.5a8a3a3d>
- Russell, S., & Norvig, P. (2021). *Artificial intelligence: A modern approach*. Pearson Education Inc.
- Santamaria, T., & Nathan-Roberts, D. (2017). Personality Measurement and Design in Human-Robot Interaction: A Systematic and Critical Review. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *61*(1), 853–857. <https://doi.org/10.1177/1541931213601686>
- Schepers, J., & Wetzels, M. (2007). A meta-analysis of the technology acceptance model: Investigating subjective norm and moderation effects. *Information and Management*, *44*(1), 90–103. <https://doi.org/10.1016/j.im.2006.10.007>
- Schmidt, P., Biessmann, F., & Teubner, T. (2020). Transparency and trust in artificial intelligence systems. *Journal of Decision Systems*, *29*(4), 260–278. <https://doi.org/10.1080/12460125.2020.1819094>
- Schunk, D. H. (1991). Self-Efficacy and Academic Motivation. *Educational Psychologist*, *26*(3-4), 207–231. <https://doi.org/10.1080/00461520.1991.9653133>
- Shavelson, R. J., Hubner, J. J., & Stanton, G. C. (1976). Self-concept: Validation of construct interpretations. *Review of Educational Research*, *46*(3), 407–441. <https://doi.org/10.3102/00346543046003407>
- Siebert, D., Godulla, A., & Wolf, C. (2021). Understanding how personality affects the acceptance of technology: A literature review. *Media and Communication*. <https://nbn-resolving.org/urn:nbn:de:0168-ssoar-75164-7>

- Smith, A. (2018). Public attitudes toward computer algorithms. *Pew Research Center*. <https://www.pewresearch.org/internet/2018/11/16/public-attitudes-toward-computer-algorithms/>
- Stuck, R. E., & Walker, B. N. (2020). Perceived relational risk and perceived situational risk scales. *Georgia Tech School of Psychology Tech Report GT-PSYC-TR-2020-01*, 27.
- Svendsen, G. B., Johnsen, J.-A. K., Almås-Sørensen, L., & Vittersø, J. (2013). Personality and technology acceptance: The influence of personality factors on the core constructs of the Technology Acceptance Model. *Behaviour & Information Technology*, 32(4), 323–334. <https://doi.org/10.1080/0144929X.2011.553740>
- Team, R. C. (2023). R: A language and environment for statistical computing. <https://www.R-project.org/>
- Tellegen, A. (1982). *Brief manual for the multidimensional personality questionnaire*.
- Tett, R. P., & Burnett, D. D. (2003). A personality trait-based interactionist model of job performance. *Journal of Applied Psychology*, 88(3), 500–517. <https://doi.org/10.1037/0021-9010.88.3.500>
- Tett, R. P., & Guterman, H. A. (2000). Situation Trait Relevance, Trait Expression, and Cross-Situational Consistency: Testing a Principle of Trait Activation. *Journal of Research in Personality*, 34(4), 397–423. <https://doi.org/10.1006/jrpe.2000.2292>
- Tschang, F. T., & Almirall, E. (2021). Artificial Intelligence as Augmenting Automation: Implications for Employment. *Academy of Management Perspectives*, 35(4), 642–659. <https://doi.org/10.5465/amp.2019.0062>
- Venkatesh, Morris, Davis, & Davis. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly*, 27(3), 425. <https://doi.org/10.2307/30036540>
- Venkatesh, Thong, & Xu. (2012). Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology. *MIS Quarterly*, 36(1), 157. <https://doi.org/10.2307/41410412>
- Venkatesh, V. (2022). Adoption and use of AI tools: A research agenda grounded in UTAUT. *Annals of Operations Research*, 308(1-2), 641–652. <https://doi.org/10.1007/s10479-020-03918-9>
- Venkatesh, V., & Davis, F. D. (1996). A Model of the Antecedents of Perceived Ease of Use: Development and Test. *Decision Sciences*, 27(3), 451–481. <https://doi.org/10.1111/j.1540-5915.1996.tb01822.x>

- Venkatesh, V., & Davis, F. D. (2000). A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. *Management Science*, 46(2), 186–204. <https://doi.org/10.1287/mnsc.46.2.186.11926>
- Venkatesh, V., Sykes, T. A., & Venkatraman, S. (2014). Understanding e-Government portal use in rural India: Role of demographic and personality characteristics. *Information Systems Journal*, 24(3), 249–269. <https://doi.org/10.1111/isj.12008>
- von Eschenbach, W. J. (2021). Transparency and the Black Box Problem: Why We Do Not Trust AI. *Philosophy & Technology*, 34(4), 1607–1622. <https://doi.org/10.1007/s13347-021-00477-0>
- Watson, H. J., & Mann, R. I. (1988). Expert Systems: Past, Present, and Future. *Journal of Information Systems Management*, 5(4), 39–46. <https://doi.org/10.1080/07399018808962939>
- Wu, K., Zhao, Y., Zhu, Q., Tan, X., & Zheng, H. (2011). A meta-analysis of the impact of trust on technology acceptance model: Investigation of moderating influence of subject and context type. *International Journal of Information Management*, 31(6), 572–581. <https://doi.org/10.1016/j.ijinfomgt.2011.03.004>
- Zhang, B., & Dafoe, A. (2019). Artificial Intelligence: American Attitudes and Trends. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.3312874>

Appendices

APPENDIX A

UTAUT 2 MEASURE MODIFIED FOR AI CONTEXT (VENKATESH ET AL., 2012)

Likert Scale: 1 = Strongly disagree, 2 = Disagree, 3 = Somewhat disagree, 4 = Somewhat agree, 5 = Agree, 6 = Strongly agree

Performance Expectancy items: PE1, PE3, PE4 [$\alpha = .88$]

Effort Expectancy items: EE1, EE2, EE3, EE4 [$\alpha = .91$]

Social Influence items: SI1, SI2, SI3 [$\alpha = .82$]

Behavioral Intention items: BI1, BI2, BI3 [$\alpha = .93$]

Performance Expectancy

PE1. I would find this AI useful in my daily life.

PE2. Using this AI increases my chances of achieving things that are important to me.

[dropped]

PE3. Using this AI would help me accomplish things more quickly.

PE4. Using this AI would increase my productivity.

Effort Expectancy

EE1. Learning how to use this AI would be easy for me.

EE2. My interaction with this AI would be clear and understandable.

EE3. I would find this AI easy to use.

EE4. It would be easy for me to become skillful at using this AI.

Social Influence

SI1. People who are important to me would think that I should use this AI.

SI2. People who influence my behavior would think that I should use this AI.

SI3. People whose opinions that I value would prefer that I use this AI.

Behavioral Intention

BI1. I would intend to use an AI like this in the future.

BI2. I would always try to use an AI like this in my daily life.

BI3. I would plan to continue using an AI like this frequently.

APPENDIX B

IPIP SCALES MEASURING CONSTRUCTS SIMILAR TO NEO-PI-R: NEUROTICISM & EXTRAVERSION

Prompt: In the following section you will find a series of statements a person might use to describe their attitudes, opinions, interests, and other characteristics. Indicate for each statement whether it is an accurate description of you. Read the statement and decide which choice best describes you. Please answer every statement even if you are not completely sure of the answer. Read each statement carefully, but don't spend too much time deciding on the answer. (Likert scale: 1 = Very inaccurate, 2 = Moderately inaccurate, 3 = Somewhat inaccurate, 4 = Somewhat accurate, 5 = Moderately accurate, 6 = Very accurate)

Neuroticism [$\alpha = .91$]

Extraversion [$\alpha = .91$]

Neuroticism

1. Often feel blue.
2. Dislike myself.
3. Am often down in the dumps.
4. Have frequent mood swings.
5. Panic easily.
6. Am filled with doubts about things.
7. Feel threatened easily.
8. Get stressed out easily.
9. Fear for the worst.
10. Worry about things.

Reverse scored:

11. Seldom feel blue.

12. Feel comfortable with myself.
13. Rarely get irritated.
14. Am not easily bothered by things.
15. Am very pleased with myself.
16. Am relaxed most of the time.
17. Seldom get mad.
18. Am not easily frustrated.
19. Remain calm under pressure.
20. Rarely lose my composure.

Extraversion

1. Feel comfortable around people.
2. Make friends easily.
3. Am skilled in handling social situations.
4. Am the life of the party.
5. Know how to captivate people.
6. Start conversations.
7. Warm up quickly to others.
8. Talk to a lot of different people at parties.
9. Don't mind being the center of attention.
10. Cheer people up.

Reverse scored:

11. Have little to say.
12. Keep in the background.
13. Would describe my experiences as somewhat dull.
14. Don't like to draw attention to myself.
15. Don't talk a lot.
16. Avoid contacts with others.

17. Am hard to get to know.
18. Retreat from others.
19. Find it difficult to approach others.
20. Keep others at a distance.

APPENDIX C

TELLEGEN'S MULTIDIMENSIONAL PERSONALITY QUESTIONNAIRE

(MPQ): SOCIAL POTENCY AND SOCIAL CLOSENESS MEASURES

Prompt: In the following section you will find a series of statements a person might use to describe their attitudes, opinions, interests, and other characteristics. Indicate for each statement whether it is 1. Very Inaccurate, 2. Moderately Inaccurate, 3. Somewhat Inaccurate, 4 Somewhat Accurate. 5. Moderately Accurate, or 6. Very Accurate as a description of you. Read the statement and decide which choice best describes you.

Please answer every statement, even if you are not completely sure of the answer. Read each statement carefully, but don't spend too much time deciding on the answer.

Social Potency: 1, 16, 25, 35, 47, 59, 71, 81, 94, 105, 117, 129, 142, 150, 163, 174, 187, 197, 206, 218, 233, 244, 257, 266, 278, 287 [$\alpha = .87 - .89$]

Social Closeness: 4, 18, 31, 45, 60, 75, 86, 99, 113, 125, 140, 152, 168, 181, 195, 208, 221, 236, 249, 263, 276, 291 [$\alpha = .85$]

APPENDIX D

PROPENSITY TO TRUST MEASURE

In this section, indicate for each statement the degree to which you agree or disagree with it as an accurate description of you. Read the statement and decide which choice best describes you. There are no right or wrong answers. (Likert scale: 1 = Strongly disagree, 2 = Disagree, 3 = Somewhat disagree, 4 = Somewhat agree, 5 = Agree, 6 = Strongly agree)

Propensity to trust: 1, 2, 3, 4 [$\alpha = .88 - .89$]

1. I usually trust people until they give me a reason not to trust them.
2. Trusting another person is not difficult for me.
3. My typical approach is to trust new acquaintances until they prove I should not trust them.
4. My tendency to trust others is high.

APPENDIX E
ACADEMIC SELF-CONCEPT MEASURE

Prompt: The following statements refer to skills or abilities that you may have. Please read each of the following statements carefully. Select the choice which indicates how much you think the statement reflects your skills and abilities.

Consider whether you have the skill or ability, keeping in mind that most people vary in the kinds of skills and abilities that they have. Avoid rating yourself the same on each skill or ability. (Likert scale: 1 = Strongly disagree, 2 = Disagree, 3 = Somewhat disagree, 4 = Somewhat agree, 5 = Agree, 6 = Strongly agree)

Verbal items: 1, 4, 8, 10, 14, 16 [$\alpha = .85$]

Math items: 2, 6, 11, 12, 15, [$\alpha = .82$]

Spatial items: 3, 5, 7, 9, 13, 17 [$\alpha = .78$]

APPENDIX F
DEMOGRAPHIC QUESTIONNAIRE ITEMS

Please respond to the following questions about yourself:

1. What is your current age in years?
2. Are you fluent in the English language?
 - a. Yes
 - b. No
3. What gender are you currently? (The following question will ask about your sex.)
 - a. Man (including Trans Male/Trans Man)
 - b. Woman (including Trans Female/Trans Woman)
 - c. Non-Binary
 - d. Other [Please specify]
 - e. Rather not say
4. What is your sex, as recorded on legal/official documents?
 - a. Male
 - b. Female
5. Are you currently a student?
 - a. Yes
 - b. No
6. What is your employment status?
 - a. Full-Time
 - b. Part-Time
 - c. Other
7. What is the highest level of education you have completed? Please type in the box below:

APPENDIX G

AI ADOPTION VIGNETTES

Prompt: Artificial intelligence (AI) is often used in technologies to help us make various decisions. For example, Google Maps and Waymo use complex models to suggest the best routes to get you to a destination. ChatGPT can provide numerous suggestions with simple prompts. When using these tools, you can decide whether you wish to take their suggestions or ignore them entirely.

In the next section, you will be presented with 22 brief scenarios where you are given the opportunity to use AI tools to assist you. Imagine yourself in each scenario provided and consider whether you would intend to use the AI tool described in it. Following each scenario, you will be asked a series of questions about your thoughts toward the AI described.

Please answer each question as if these situations and tools are real.

SCENARIOS

Extraversion

Vignette 1: You need to form a group to complete an assigned project and you are presented with the opportunity to use an AI tool for this. If you choose to use the device, the AI will determine two peers who best fit your personality and select them for your group.

Vignette 2: You are interested in making new friends and have access to an AI device that can connect you with new people. If you decide to use this device, it will determine your compatibility with someone else based on your personality and interests and will put you in contact with them.

Vignette 3: You are interested in going on the online dating market and need to set up your dating bio. You have access to an AI that will write your bio for you given a few

prompts about yourself. If you decide to use this device, it will generate and apply your bio.

Neuroticism

Vignette 1: You are expected to give a brief speech on a sensitive topic to a diverse audience. You are aware of an AI device that will edit your speech for clarity and appropriate language. If you choose to use this device, it will revise your speech accordingly.

Vignette 2: You have applied for two jobs and received an offer from both that have similar characteristics and find yourself uncertain about which to choose. You are aware of an AI device that will determine the better choice for you based on your credentials and preferences. If you choose to use this device it will make this decision for you.

Vignette 3: Today you and a colleague had a disagreement in a regularly scheduled meeting leading to tension between you and your colleague. You are presented with an AI device to assist you with processing this interaction. If you choose to use this AI, it will converse with you to provide specific strategies for resolving the tension around this encounter.

Verbal Ability

Vignette 1: You need to write an email indicating that you have to miss a business day due to unforeseen circumstances. You are presented with an AI that will write an email for you based on a few prompts that you provide it. If you choose to use this device, you will provide the prompts and it will generate an email.

Vignette 2: You need to write a cover letter for a job opening that was recently posted. You are presented with an AI that will write a draft for you based on a few prompts that you provide it. If you choose to use this device, you will provide the prompts and it will generate a letter.

Vignette 3: You need to read and summarize an empirical research article. You are presented with an AI that will scan the contents of the paper and create a summary of the paper for you. If you choose to use this device, it will provide a bulleted summary of key

points.

Math Ability

Vignette 1: You need to create a monthly budget and you are presented with an AI device that will calculate and maintain your monthly spending budget based on the parameters you provide as well as your ongoing spending habits.

Vignette 2: You are cooking for five people using a recipe that only cooks for two people. You have access to an AI tool that can scan images and adjust the measurements of a recipe for a different number of people. If you choose to use this, it will adjust the measurements accordingly.

Vignette 3: You are working on a project that involves interpreting a set of data. You have access to an AI tool that can generate these insights for you. If you choose to do this it will generate a report detailing interpretations of the data.

Spatial Ability

Vignette 1: You are buying new furniture and decorations for your room, and you have access to an AI device that can scan the room and assist you with this. If you choose to use this device, it will purchase decorations within your budget based on your selected style preset.

Vignette 2: You have the parts to build a simple piece of furniture and are presented with an AI to help you build it. If you choose to use this device, it will evaluate the pieces and determine how you should construct the furniture.

Vignette 3: You need to design a flyer to post around campus for a club event. You have access to an AI that will create a final flyer design based on the information you provide it. If you choose to use this device, it will design the flyer for you.

Organizational Ability

Vignette 1: You need to organize and prioritize your tasks for the week and are presented with an AI that will assist you. If you choose to use this device, it determines what tasks are most to least important and organizes them accordingly.

Vignette 2: You decide to organize your email inbox and are presented with an AI to assist you. If you choose to use this device, it will determine the logical organization of your emails by topic and adjust your inbox accordingly.

Vignette 3: You need to break down a task into sub-tasks that are more manageable and are presented with an AI that will assist you. By providing the AI with the tasks you need to complete, it will automatically break them down into manageable sub-tasks.

Neutral Contexts

Vignette 1: You need to get to a particular destination and there is an AI device that will assist you. If you choose to use this device, it will determine the most efficient route and present it to you.

Vignette 2: You are interacting with an entertainment streaming service and can use AI to help recommend new shows. If you choose to use this device, it will determine the next show for you to watch based on your interests and previous viewing history.

Liability Varied Contexts

High: You are choosing to purchase a new car. A manufacturer has introduced an AI-enabled self-driving option that will operate the car largely without your input. The manufacturer makes claims about the safety of the AI system, but in the event of any accident, even if the AI-enabled system is engaged, you bear the ultimate responsibility (liability) for any accident.

Low: You are choosing to purchase a new car. A manufacturer has introduced an AI-enabled self-driving option that will operate the car largely without your input. The manufacturer is so certain of the AI system, if it causes an accident, the manufacturer will assume liability if the AI system was engaged at the time of the accident.

High: You are presented with a grocery AI assistant that analyzes your purchasing patterns and needs and orders groceries for you. If you use the AI assistant, you will receive a 15% discount on all groceries. If it gets your order wrong, you will be expected to pay for these items anyway.

Low: You are presented with a grocery AI assistant that analyzes your purchasing patterns and needs and orders groceries for you. If you use the AI assistant, you will receive a 15% discount on all groceries. If it gets your order wrong, the AI software developer will reimburse you for the unwanted items that were ordered.

APPENDIX H
COMMITMENT AND EFFORT CHECK QUESTIONS

(Beginning of Survey) Commitment Statement Data quality is important to informative research. Do you agree to read each question carefully and respond to the best of your ability? Please type “Yes” or “No” in the box below. By doing so you are also verifying that you are the individual taking this survey.

(End of Survey) Effort Check Did you expend effort and attention sufficient to warrant using your responses for this research study? Please type “Yes” or “No” in the box below.