Substantive Use of Artificial Intelligence: The Role of Individual Differences

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Abstract English

Artificial intelligence (AI) is becoming increasingly powerful, enabling users to perform tasks more efficiently and effectively. However, not all users are equally able to take advantage of its capabilities. We draw on previous literature that has introduced the concept of “substantive use” – the reflective consideration of how to use a system's features – to better understand individual differences in the context of AI. We contribute to the current literature in three ways: First, we summarize the literature on technology use and describe its relevance for AI-related research. Second, we review the literature and show that IS has already begun to investigate individual differences to understand the use of AI systems. Third, we propose a theoretical model that accounts for the direct and configurational effects of individual differences on substantive use behavior.

Abstract Deutsch

Künstliche Intelligenz (KI) wird immer leistungsfähiger und ermöglicht es den Nutzern, Aufgaben effizienter und effektiver auszuführen. Allerdings sind nicht alle Benutzer gleichermaßen in der Lage, diese Fähigkeiten zu nutzen. Wir stützen uns auf frühere Literatur, die das Konzept "substantive use" eingeführt hat – die Überlegung, wie die Funktionen eines Systems genutzt werden können –, um individuelle Unterschiede im Kontext von KI besser zu verstehen. Wir tragen auf drei Arten zur aktuellen Literatur bei: Erstens fassen wir die Literatur zur Nutzung von Technologie zusammen und beschreiben ihre Relevanz für die KI-bezogene Forschung. Zweitens sehen wir die bestehende Literatur durch und zeigen, dass die Forschung im Bereich Wirtschafsinformatik bereits damit begonnen hat, individuelle Unterschiede zu untersuchen, um die Nutzung von KI-Systemen zu verstehen. Drittens schlagen wir ein theoretisches Modell vor, das die direkten und konfigurativen Auswirkungen individueller Unterschiede auf „substantive use“ berücksichtigt.

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1. Introduction

It is hard to overstate the impact of machine learning (ML) and artificial intelligence (AI) in academia and in practice. In Information Systems (IS) research, several AI-related special issues have been published (Berente et al., 2021; Benbya, Strich and Tamm, 2024), and all leading conferences, including the “International Conference on Wirtschaftsinformatik”, have addressed the impact of AI in various domains, such as its impact on human-computer-interaction.

A fundamental promise of current advances of AI is the increase in performance. From a technological perspective, this progress is well documented. Modern machine learning models exceed the performance of previous generation by far. For example, the current version of GPT outperforms its predecessors in many ways. Similarly, the current literature has shown how ML and AI can be used to create business value (Shollo et al., 2022).

Despite all the optimism surrounding AI, the IS literature to date has repeatedly shown that technology cannot be used equally by all individuals. In fact, most re-search suggests that there are significant individual differences when it comes to technology use. For example, studies have shown that individual traits such as being mindful with IT, are significantly related to technology adoption (Thatcher et al., 2018). However, our literature review (see Section 3) shows that there is a paucity of research that has integrated the effects of individual differences with substantive use of technology with AI. As a result, there is a lack of theoretical knowledge to inform how to promote substantive use of AI or how to support individuals who struggle to do so.

We seek to address this important issue and contribute to the existing literature in three ways: First, we review the existing literature on technology use and identify the conceptualization of substantive use as the most promising for theorizing in the field of AI. Second, we consolidate the current literature on individual difference traits and identify those most relevant to AI research. Finally, we propose a conceptual frame-work that allows scholars to study substantive use behavior for AI. Integrating previous literature, our conceptual model integrates two mechanisms: 1) isolated impact of individual difference traits on substantive use, and 2) configurational impact of individual difference traits on substantive use.

The paper is structured as follows: In section 2.1, we review previous literature that has conceptualized system use in order to identify the most promising conceptualization for the domain of AI. In section 2.2, we demonstrate the suitability of substantive use of technology through an example in the application of Explainable AI (XAI). Section 3.3 is devoted to previous literature on individual differences. In section 3, we will present the methodological approach used to review the current literature on the intersection of AI use and individual differences. We discuss the results of this study in section 4 and provide an outlook for future research in section 5.

2. Related Work

2.1. Conceptualizations of system use construct

The “(system) usage” construct is arguably one of the most widely disseminated construct in IS research. It is the fundamental dependent variable in the technology acceptance and adoption stream (Venkatesh et al., 2003) and has been applied in various domains and with different applications (Venkatesh, Thong and Xu, 2016). It has also undergone various reconceptualizations that recognize the richness of the construct. For instance, it has been shown that system use can be measured with different degrees of richness, recognizing three domains: user, task, and system (Bur-ton-Jones and Straub, 2006). This conceptualization has paved the way for more comprehensive conceptualizations of (system) use. Other studies have suggested that technology use is best understood when it is conceptualized as interaction behavior, which has been conceptualized as a use-related activity (Barki, Titah and Boffo, 2007). Others have emphasized how features of a particular technology are used (Jasperson, Carter, and Zmud, 2005), with a particular focus on how users change their IT use after the adoption phase (Bagayogo, Lapointe and Bassellier, 2014). To better understand how and why users use specific features of an information system, the concept of adaptive use has been proposed and evaluated (Sun, 2012). More recently, it has also been argued that the use construct should be studied beyond a specific domain, such as the work domain, and instead should be conceptualized as an overarching construct that spans multiple domains. For this reason, the notion of transgressive use has been suggested (Klesel et al., 2017). An overview of conceptualizations of technology use is provided in Table 1.

Concept	Method	Technology
Substantive use behavior (Jasperson, Carter and Zmud, 2005)	Conceptual	No specific technology
System usage (Burton-Jones and Straub, 2006)	Survey	Microsoft Excel
IS-related activity (Barki, Titah and Boffo, 2007)	Survey	No specific technology
Adaptive use (Sun, 2012)	Survey	Microsoft Office
Enhanced use (Bagayogo, Lapointe and Bassellier, 2014)	Grounded Theory	No specific technology
Transgressive use (Klesel *et al.*, 2017)	Case Study	No specific technology

Table 1: Overview Conceptualizations of Technology Usage

Most studies that have examined the nature of system use have taken a technology-agnostic perspective or have focused on Microsoft Office products such as Microsoft Excel. While these conceptualizations arguably have a different emphasis on specific aspects, most concepts allow for a more nuanced perspective on how individuals use technology with respect to specific features. This is made very explicit in the notion of substantive use (Jasperson, Carter and Zmud, 2005), adaptive use (Sun, 2012), and the notion of enhanced use of technology (Bagayogo, Lapointe and Bassellier, 2014), where the authors examine specific features of a class of systems.

While we acknowledge that there is an ongoing discourse on the conceptualization of one of the most fundamental constructs of the IS discipline, we also note that there is only little research available that has re-evaluated the suitability of current conceptualizations with modern technologies such as AI. For this reason, we will now review why AI is a class of systems that requires a contextualized form of the use construct.

2.2. System Use with AI technologies

In a number of studies, authors have argued that AI systems have distinct characteristics that distinguish them from existing systems. Research has also shown that people confronted with AI are often influenced by what is known as “algorithm aversion” (Turel and Kalhan, 2023). Consequently, it has been argued that new ways of managing AI is needed to realize the potential of AI technologies in organizations (Berente et al., 2021).

IT management can be studied from different levels, which means that the investigation of AI can also be conducted with a focus on the entire organization or at the individual level. While there is a rich body of knowledge that investigates IT management at the firm level (Li et al., 2021), most research on adoption takes an individual perspective. In particular, research that focusing on human-computer-interaction is typically conducted at the individual level. Therefore, in the following, we also focus on the individual level.

AI technologies are ubiquitous and can be found in a wide range of applications. Therefore, we use a specific human-computer interface (HCI) example which is used to demonstrate that a specific contextualization of the use construct is required. We use a simplified AI-based fraud detection dashboard that allows users to identify fraudulent documents (see Figure 1). While this example is simplified, it contains all basic and necessary components. It includes a machine learning model (i.e., for classification) and an Explainable AI (XAI) component that allows users to learn more information about the decision made by the system. In this case, words that increase the likelihood of a fraud case are highlighted (red, underlined). This type of dashboard has previously been developed and evaluated in the IS literature to study hate speech (Meske and Bunde, 2022), diabetes self-management (Van Der Waa et al., 2021), and signature forgery detection (Hamm et al., 2023). The XAI module is most commonly implemented using SHapley Additive exPlanation (SHAP values) (Lundberg and Lee, 2017; Lundberg et al., 2020).

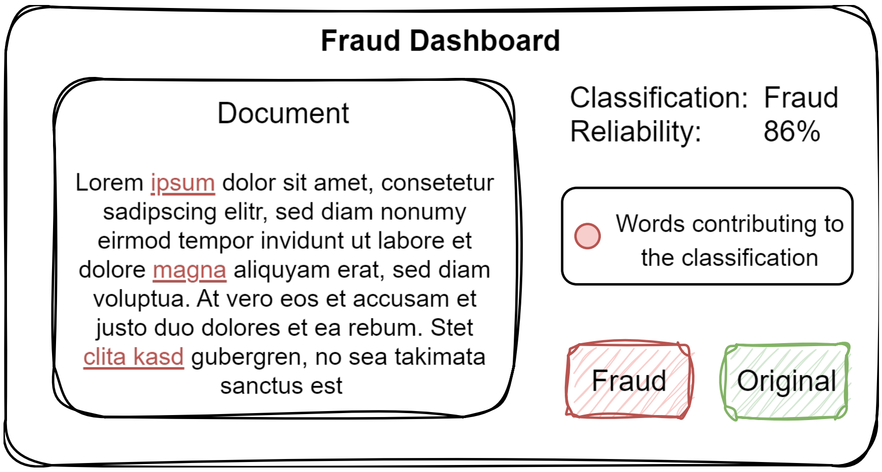

Figure 1: An Example of an AI-based Fraud-Detection Dashboard

Given the prior literature on algorithmic aversion, the use of an AI-based dash-board may vary significantly from user to user. For example, a user may completely distrust the system and ignore it altogether. Alternatively, a user may be guided by a so-called automation bias and use the information provided without further elaboration. To conceptualize the use of AI, we draw on previous literature. In particular, we acknowledge the notion that system use is an interplay between a user, a task, and an (AI) system (Burton-Jones and Straub, 2006). Furthermore, we adapt the notion of substantive use (Jasperson, Carter and Zmud, 2005), which is defined as “an individual’s reflective consideration to use a single feature (or a select subset of features) available in an IT application” (Jasperson, Carter and Zmud, 2005, p. 535). In the context of our example, the deliberate use of the XAI component would be considered as an example of substantive use.

There are at least two fundamental reasons why we argue that a substantive use of an AI-based system is preferable: First, the literature has shown that engaged behavior leads to positive outcomes. For example, a mindful use of technology has been shown to be positively associated with outcome variables (Thatcher et al., 2018). As a result, substantive use of an AI system is preferable. Second, prior literature has shown that users who are not engaged are more likely to produce errors (Reason, 1990). This is particularly relevant for AI applications, because they are often used to support decision making in high-stakes situations, such as diagnostic decisions in medical contexts (Jussupow et al., 2021).

There is preliminary evidence that the use of AI dashboards is influenced by contextual variables. In the field of XAI, it has been shown that there are differences in outcome variables depending on the type of XAI (Van Der Waa et al., 2021). Others have shown that socio-demographic variables are also relevant when it comes to how users engage with AI-based systems (Hamm et al., 2023). However, there is a significant gap in terms of a comprehensive understanding of the relative importance of contextual variables and their impact on AI use. Against this background, we proceed with a review of individual differences that allows to address this gap.

2.3. Individual Differences

Individual differences are relatively stable characteristics of individuals that persist across time and context, although stability does not imply that they are unchangeable (Sackett et al., 2017). Differential psychology has traditionally studied individual differences and their assessment. Here, we focus on the most important among these traits. However, determining the number of traits that exist is not a straightforward task. There are more than several hundred traits, some of which have been labeled differently by different researchers and research traditions, even though they are essentially very similar (Cooper, 2019). Trait taxonomies have been developed to organize findings in the field. One of the most well-known models is the Big Five fac-tor model of personality. In this model, personality is divided into five higher order factors, including conscientiousness and agreeableness, which are further divided into lower order facets (Crowe, Lynam and Miller, 2017). The most commonly studied dispositional characteristics include ability, interest, and personality (Lubinsky, 2000).

To identify the most important of these traits, we reviewed studies published in leading differential psychology journals, including the "Journal of Personality and Social Psychology", "Personality and Individual Differences", and "Psychological Bulletin". By excluding traits unrelated to technology use (e.g., psychopathological traits, vocational interests, and psychomotor abilities), we narrowed the traits to a manageable number and arrived at a list of six traits (see Table 2).

Trait	Domain	Definition
General Intelligence (Jensen, 1999)	Cognitive ability	General problem solving ability
The Big Five (e.g., conscientiousness; Costa and McCrae, 1999)	Personality	Enduring characteristics and behavior that make up a person's adjustment to life.
Achievement Motivation (McClelland, 2015)	Motivational	Motivation to accomplish and maintain high standards.
Goal Orientation (Diener and Dweck, 1978)	Motivational	Motivation to direct behavior towards attaining goals.
General Self-efficacy (Schwarzer and Jerusalem, 1995)	Motivational	Individuals' perceptions of their ability to perform across various situations.
Need for Cognition (Cacioppo and Petty, 1982)	Motivational	Individuals' tendency to engage in and enjoy effortful cognitive endeavors.

Table 2: Group characteristics

Although the number of mental abilities is virtually unlimited, the application of factor analysis to mental ability tests yields only a few common factors. These are typically labeled verbal, spatial, numerical and mechanical reasoning, and memory ability. The higher-order factor reflected in the variance of all mental abilities is called general mental ability or "g" (Jensen, 1998), a construct that is predictive of performance such as job performance and training success (Salgado et al., 2003). Personality is thought of as a person's dispositional traits or trait patterns that constitute their adjustment to life (VandenBos, 2017). The five-factor model of personality is now widely accepted. The Big Five model organizes personality into five broad factor-analytically derived categories, commonly referred to as extraversion, neuroticism (or negative affectivity), conscientiousness, agreeableness, and openness to experience (Costa and McCrae, 1999). Conscientiousness, for example, refers to the tendency to follow rules, to be goal-directed, and to delay gratification. The final category is motivational traits. These are stable individual differences in preferences related to approach and avoidance mediating the effect of personality and cognitive ability on behavior (McCabe and Fleeson, 2015).

3. Methodology

3.1. Structured Literature Review

To investigate the relationship between traits and AI use in the HCI literature, we conducted a literature search using the Scopus database. Scopus is a leading abstract and citation database of peer-reviewed research literature. For our review, we consulted the "Senior Scholars' List of Premier Journals" and added important HCI journals such as "Computers in Human Behavior" and "Transactions on Human-Computer Interaction". We also included the proceedings of the "International Conference on Information Systems." We used relevant keywords to perform a comprehensive search, using in the following query:

TITLE-ABS-KEY ("AI" OR "Artificial Intelligence" OR "Algorithm Aversion" OR "Chatbot" OR "LLM" OR "Large Language Model" OR "Large-Language Model" OR "XAI" OR ("Explainable" AND "AI")) AND TITLE-ABS-KEY ("Trait*" OR "General Intelligence" OR "Big Five" OR "Big-Five" OR "OCEAN" OR "Extraversion" OR "Openness" OR "Conscientious*" OR "Neuroticis*" OR "Neurotic" OR "Emotional Stab*" OR "Agreeable*" OR "Achievement Need*" OR "Need for Achievement" OR "Achievement Motivation" OR "Goal Orient*" OR "Need for Cognit*" OR "Self-Efficacy" OR "Need for Cognition" OR "Cognition Need" OR "Intellectual Abilit*") AND EXACTSRCTITLE ({Decision Support Systems} OR {European Journal of Information Systems} OR {Information & Management} OR {Information and Organization} OR {Information Systems Journal} OR {Information Systems Re-search} OR {Journal of the AIS} OR {Journal of Information Technology} OR {Journal of MIS} OR {Journal of Strategic Information Systems} OR {MIS Quarter-ly} OR {International Conference on Information Systems} OR {Computers in Hu-man Behavior} OR {Transactions on Human-Computer Interaction})

All reviewed articles are retrieved with the above query in the first quarter of 2024. The query returned 32 documents. After screening the abstracts, we retained 3 documents (see Table 3).

Publication	Trait(s)	Findings
Rabl, Petzsche, Baum and Franke, 2023	Self-efficacy	Self-efficacy does not moderate the effect of support by decision support systems (DSS) on intrapreneurial behavior.
Neumann, Niessen and Meijer, 2023	Personality (Conscientiousness) and cognitive ability	More dutiful participants and those with higher cognitive ability reach out for algorithmic advice more often.
Erskine, Khojah and McDaniel, 2019	Self-efficacy and cognitive ability	Self-efficacy did not predict better performance using heatmap features in dashboards.

Table 3: Results of the Literature Review

3.2. Results

Most of the research identified does not address how users engage with AI systems, and how they do or do not take advantage of opportunities to achieve high levels of substantive use. Instead, the research focuses on outcome variables such as trust (e.g., Montag, Kraus, Baumann and Rozgonjuk, 2023), threat perception (Stein et al., 2019), moral considerations (Pauketat and Anthis, 2022), intention to use (Chuah et al., 2021), or perceived effectiveness (Ben-Zvi, 2012). While these studies have their own merits, they largely neglect the substantive use of AI. Rabl et al. (2023) investigate how decision support systems (leveraging machine learning and prediction) affect intrapreneurial behavior using a conjoint study. However, they do not find evidence to support their hypothesis that self-efficacy moderates the effect of DSS use on behavior. Neumann et al. (2023) postulated that dutiful decision makers (dutifulness is a facet of trait conscientiousness) more consistently use available algorithmic advice in a hiring context. Dutifulness is moderately correlated with using algorithmic advice, judgment consistency, and predictive validity in their experiment. Erskine et al. (2019) hypothesize that self-efficacy would be related to perceptions of task-technology fit in a geospatial application and indirectly increases decision accuracy and decision time for location decisions, but their hypothesis was not supported. The same is true for their hypothesis regarding cognitive ability. In conclusion, there is very little research on how individual differences affect user engagement and use behavior, especially for AI-based interfaces and dashboards. Understanding how users may or may not take advantage of the AI system (i.e., high levels of substantive use) based on their individual dispositions has only received little attention.

4. Discussion

We argue that the patterns of use and consequently the performance that individual users achieve with AI systems are influenced by individual characteristics, such as differences in ability, personality, and motivation. This perspective is consistent with the “second digital divide” perspective (DiMaggio et al., 2004), which emphasizes the importance of individual factors in relation to use behavior. There are two distinct perspectives on how traits can relate to system use and the performance that users can ultimately achieve when using AI systems: 1) isolated (direct) impact on use, and 2) complex interactions of traits. Figure 2 provides a conceptual overview of how traits influence substantive use in these two ways.

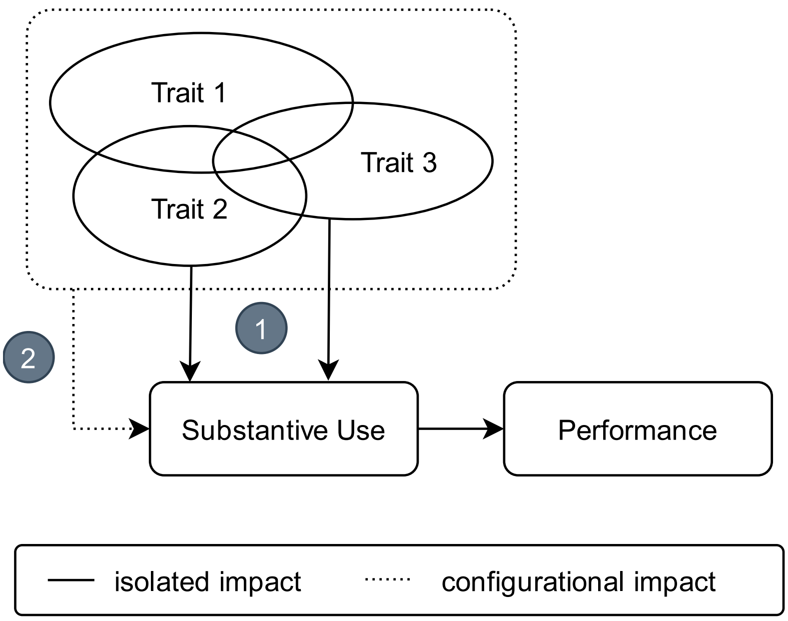

Figure 2: An Integrated Model of Substantive Use and Traits

In the first perspective, termed “isolated impact” traits are envisioned as antecedents of use. We take an example from the domain of personality. A more conscientious user, a trait characterized by thorough elaboration, is likely to scrutinize an interface and find options that other users may not. Users with high levels of conscientiousness are also more likely to read instructions and to study learning materials in order to increase their ability to master the interface and control the system. Consider a dermatologist who is given access to a skin screening tool that uses AI to detect alarming skin conditions. The system’s features can be learned and mastered better by a more conscientious dermatologist than by a less conscientious one. This example shows that there can also be an indirect link between traits such as conscientiousness and use through motivational traits such as goal-orientation. A highly conscientious dermatologist may be motivated to learn, acquire new skills, and be goal-oriented, ultimately leading to increased use of the system. Similarly, other motivational traits, such as the need for cognition, which is the tendency to enjoy cognitively effortful activities, may affect the way a user interacts with an AI. For example, when prompting a text-to-image generator, people who enjoy thinking will be motivated to experiment with different formulations rather than settle for the first best answer. This allows them to get the most out of the system and produce better results. In addition, individual differences can either facilitate or hinder the impact of the interface on use. Interfaces for AI systems can differ in the options available to users and how they are presented. For example, Adobe Firefly, a text-to-image generator, has a wide range of options readily available in its interface. The interface for DALL-E, on the other hand, is more basic, but it allows the same customization through text input. Or consider a recommendation system for making decisions about store locations. The most effective way to present location recommendations may vary. For example, a system could provide a choice of plotting points or displaying a heat map with color coding to indicate uncertainty. How the presentation of input options or the presentation of results translates into use may depend on individual differences. Using the example of need for cognition (Cacioppo and Petty, 1982), a user who scores low on this trait might prefer simple visualizations and rely on pre-selected options. In contrast, a user who scores high on need for cognition would want to acquire more information and would be curious about available advanced settings or options and how they affect the output of a system.

In the “complex interaction of traits” perspective, we argue that traits interact in complex ways and affect technology use as a complex composition. In fact, personality traits do not only operate in isolation, but rather interact with other traits to influence a person’s behavior. This perspective is well supported by personality research (Grant and Langan-Fox, 2006). One trait can interact with another to create a specific configuration that shapes perception of and motivation for an interface. A user with a profile of high conscientiousness and high neuroticism may be thorough in evaluating the features offered, but easily distracted by setback. Therefore, the two traits may cancel each other out, resulting in this user profile being neither predisposed to high nor low levels of substantive use. Methodologically this perspective is reflected in the literature on configurational thinking (Misangyi et al., 2017), which has received considerable attention in the IS domain (El Sawy et al., 2010; Park, Fiss and El Sawy, 2020). Thus, methods such as fuzzy-set qualitative comparative analysis (fsQCA) could be used to study the necessary and sufficient trait configurations for substantive use (Fiss, Cambré and Marx, 2013).

When investigating traits that affect usage behavior, it is probably wise to start with traits that are relatively close to behavior. For example, motivational traits are more closely related to behavior than personality or even more so than cognitive ability, because they represent not only what people are capable of, but also how they typically use their predispositions and behave in certain ways. Thinking about dispositions, such as the need for cognition, are interesting in this regard. The need for cognition is related to both personality and cognitive ability (Fleischhauer et al., 2010; Cacioppo and Petty, 1982). It predicts exploratory behavior, diminished uncertainty aversion, and increased persistence, and is thus highly relevant in the context of substantive use of AI systems.

Regarding context, we believe that Explainable AI (XAI) is of particular importance. The goal of XAI is to promote shared performance between the AI system and the user and to increase confidence in predictions, thereby encouraging and enabling high levels of substantive use. A meaningful explanation of the output of AI systems depends on users’ expectations, their ability to understand them, and their motivation to process them. Therefore, it is reasonable to assume that personality and motivational traits affect expectations and motivation to engage with explanations. A user who is more conscientious or motivated to analyze evidence expects more detailed explanations and is more willing to process and use them. Cognitive abilities, on the other hand, may play a crucial role in processing explanations and understanding how they contribute to the evaluation of outcomes. Thus, we believe that XAI is an excellent starting point for understanding the role of individual differences in substantive use.

5. Outlook

Artificial intelligence is here to stay. Therefore, theorizing about AI use and acknowledging individual differences is an important area of research that allows us to better understand human behavior with

AI and also paves the way for designing better AI-based applications. In this study, we have reviewed existing conceptualizations and argued for a more thorough conceptualization and consideration of substantive use for AI systems. In addition, we reviewed the existing literature on individual differences traits and proposed a conceptual model that integrates both streams of re-search into an integrated model that highlights two important mechanisms, namely isolated impact and a configurational impact. Because the focus of this study is conceptual, it invites future research to empirically investigate substantive use in the context of AI. Among other things, future research could use substantive use and investigate how it can be manipulated in an experimental setting. In this regard, the use of XAI would be a well-suited point of departure. Finally, we encourage future research to integrate user traits to understand the substantive use of AI systems. Investigating the impact of traits holistically using configurational theories is a promising area of research to gain a better understanding of substantive use.

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