competence, benevolence, and integrity

(e.g., Nilashi

et al ., 2016; **Qiu** & 103 **Benbasat, 2009; Wang & Benbasat, 2007, 2008** 13

, 2009, 2016; Wang et al., 2016; Xu et al., 2014).i For example,

Wang and Benbasat (2007) empirically verified **the important role of explanation facilities in** the 229 **initial**

trust-building process and found that

different types of explanations influence **different trusting beliefs: how explanations** enhance 34 beliefs regarding **competence and benevolence** , why explanations enhance **beliefs**

regarding benevolence, and trade-off explanations enhance beliefs regarding integrity. In a further investigation of transparent RAs, Wang and Benbasat (2016) demonstrated that perceived transparency through the provision of explanation facilities positively influences all three trusting beliefs. Xiao and Tan (2012) found that explanation facilities mitigate consumers' perceived deceptiveness of RAs via the mediating effects of perceived transparency. Focusing on issues of recommendation neutrality in biased RAs, the second stream of research has empirically examined the effects of disclosure designs, such as product-sponsorship disclosure (Wang & Wang, 2019; Wang et al., 2018a), warning messages (Xiao & Benbasat, 2015), and rating displays (Adomavicius et al., 2019a), and their consequences, including perceived transparency, perceived integrity, perceived bias, trust, and distrust.ii However,

to the best of our knowledge, no study has holistically investigated **the effects of** revealing 209 **and**

explaining both recommendation mechanisms (e.g., their how or why) and recommendation bias (e.g., sponsored recommendation) via an integrated model. Moreover, no study has empirically explored the differential effects of explicitly revealing the three predominant RATs on user perceptions. Our study aims to fill this void by developing an affordance-based integrated model and empirically testing the model on a real e-commerce RA (i.e., Amazon's recommendation engine) using a novel FSM. 2.2. Toward an Affordance-Based Integrated Model Given the similarities in the two research streams' focus on revealing and explaining the inner workings of the RA black box, it is theoretically plausible and empirically feasible to build and test an integrated model that includes both research streams' core constructs (i.e., perceived transparency, perceived integrity, perceived deceptiveness, trust, and distrust). Moreover, prior research has focused on the effects of unsealing the black box on users' initial trust/distrust and perceptions, but no study has investigated users' 104 PDC with RAs from a long-term relational perspective. Therefore, building on

Wang and Benbasat (2007), **Wang et al** . (2018a), **and** Wang **et al** 129

. (2018a), we integrated the affordance theory,

the theory of social responses to computers (TSRC), **and the** 58

two-process view of trust and distrust to develop a contextualized conceptual model (Figure 2) with which to examine the relationships among RA artifacts, explaining affordances, users' perceptions, and PDC. Through the affordance lens, we first defined the salient explaining affordances provided by two closely related UI artifacts: RAT disclosure and sponsored-recommendation disclosure. We then used the TSRC to explain how the two explaining subaffordances (i.e., the RAT-explaining affordance and the AI bias- explaining affordance), when they are actualized, influence perceived effectiveness, perceived transparency, perceived integrity, and perceived deceptiveness. According to the TSRC, users treat computer-based agents

as social actors and apply social rules to them 33

in the process of forming social relationships that involve trust (Reeves & Nass, 1996). We further incorporated a two-process view

into the model to simultaneously **examine the effects of** the aforementioned perceptions **on** 314

trust and distrust, proposing that trust and distrust, in turn, influence an individual's PDC with an RA. The

two-process view proposes that the formation **of trust and distrust** are distinct **processes** 9 that can be influenced by the same factors in different ways (Komiak & Benbasat, 2008). We expect that integrating these theoretical perspectives will provide a more holistic conceptual foundation on which

to develop a contextualized **understanding of the effects of** unsealing **the** 300

black box of an AI-powered RA. The following sections provide a detailed presentation of these theoretical perspectives. 2.3. Affordance Theory Originally developed in ecological psychology to examine an actor's action possibilities in a given environment, Gibson (1977, 1979) affordance theory has received renewed attention from IS scholars, because its application has provided new insights into the relationships between IT artifacts and users in various domains (

e.g ., Chan **et al** ., 2019; Karahanna **et al., 2018** ; Krancher **et al** ., 2018; Seidel **et al** ., 2013; Steffen **et al** ., 2019; Sun **et al** ., 2019; Vaast **et al., 2017** 113

). Most notably, Norman (1999; 2013) adapted 105 Gibson's affordance theory to the technology context and defined affordances as relationships between an object's properties and an agent's capabilities

that determine how the specific **object could possibly be used** 63

. Krancher et al. (2018) pointed out that the affordance perspective has four key areas of concern: (1) the nature of actions, (2) the potential for action between actors and objects, (3) how artifacts facilitate actions, and (4) the role of actors' objectives and goals. The core

tenet of affordance theory is that technological capabilities are 295

part of the relationship between users **and technological artifacts in specific** 3

situations rather than independent technological functions or features (Leonardi, 2011; Suh et al., 2017). The

link between technology features and user goals creates **a** relational **lens** with which **to examine why users would actually use** 81 a given technology (Steffen et al., 2019).iii Affordances are actualized when users employ them

to achieve immediate concrete outcomes that support their goals 2

(Burton-Jones & Volkoff, 2017). Chan et al. (2019) reaffirmed the relational nature of affordances by identifying four affordances of social networking sites (SNSs) – accessibility, information retrieval, editability, association – and examining

their effects on the environmental conditions conducive to SNS bullying 2

. They empirically demonstrated that affordances play a salient role

in giving rise to the favorable evaluation of criminogenic opportunities 2

(Chan et al., 2019). Because SNS and RA systems share similar boundary conditions, we argue that it is theoretically plausible and empirically feasible to apply affordance theory to the context of AI-powered RAs and use its relational lens to explain the effects of unsealing the black box of intelligent RAs. 2.4. The Construct of the Explaining Affordance and Its Subaffordances Drawing on affordance theory and prior theoretical perspectives on transparent RAs, we identify the explaining affordance and define it as a salient RA affordance that enables users to learn, on the basis of an understandable language, about an RA's inner workings, including why and how certain items are recommended and how the underlying algorithm works in terms of functionality and recommendation neutrality. Following Volkoff & Strong's (2017) principles for using affordance theory in IS research, we use a participle ("explaining") to name the construct. To better conceptualize and operationalize this novel 106 construct, we separate the explaining affordance into two subaffordances: (1) the RAT-explaining affordance (REA) and (2) the bias-explaining affordance (BEA). We argue that when these subaffordances are actualized by a goal-oriented user, they have the potential to influence the user's perceptions of the RA. 2.4.1. Recommendation-Algorithm-Type-Explaining Affordance We define the REA as

the extent to which a user perceives **that an** RA provides an **opportunity to** understand **the** 2

different recommendation mechanisms and how and why certain items are recommended to them. We draw

on cognitive learning **theory** (CLT) **to** explore **the effects of** an actualized REA **on** 294

user

perceptions. CLT explains how the human mind works while people learn, focusing on how information is processed by the brain (Piaget, 1985). It posits that learning occurs through the internal processing of information, based on the notion that people mentally process the information they obtain, instead of simply responding to stimuli from their environment (Piaget, 1985). According to CLT, explanation facilities help users evaluate RAs appropriately for two reasons: (1) explanations promote the cognitive assessment of decision aids (how and why) by improving the understandability of RAs (Wang & Benbasat, 2007), and (2) explanations help users evaluate a decision aid as they facilitate behavioral assessments (guidance) of the aid by helping users properly utilize its capabilities (Silver, 1991). Wang and Benbasat (2009) empirically confirmed the role of explanation facilities in enhancing users' perceptual evaluations of RAs. In the context of AI-powered RAs, the most common RAT typology is based on three types of recommendation-filtering algorithms (Balabanović & Shoham, 1997; Xiao & Benbasat, 2007), which recent technological advancements in the techniques of deep learning and natural language processing (Adomavicius & Tuzhilin, 2005; Gill, 2019; Tilahun et al., 2017; Zhang et al., 2019) have significantly enhanced. Content-based filtering (CBF). This RAT recommends similar items to users by employing a user-modeling process to infer users' interests and preferences from the items with which users interacted previously (Beel et al., 2016; Xiao & Benbasat, 2007, 2014b). The history of a user's interactions enables the system to (1) display recently recommended and viewed items to direct the user's attention back to these items, (2) filter out items the user has already purchased or watched, and (3) serve as a training dataset 107 for the AI algorithm that builds the user model (Beel et al., 2016; Bobadilla et al., 2018; Pazzani & Billsus, 2007). For example, YouTube recommends videos to viewers by analyzing their historical interests; Pandora recommends music similar to the music users have recently listened to; and Google News recommends news items based on readers' interests, preferences, and previously viewed articles. Collaborative filtering (CF). This RAT mimics the process of word-of-mouth recommendation (Ansari et al., 2000; Liang et al., 2006) by using the opinions, tastes, and preferences of like-minded people to generate recommendations (Konstan & Riedl, 2012; Qiu & Benbasat, 2009; Xiao & Benbasat, 2007). First developed by Goldberg et al. (1992), collaborative filtering is now widely used by a variety of RAs. A typical example of collaborative filtering is Amazon's RA, which often displays the text "customers who bought this item also bought." The CF approach introduces referrals among products by linking them to each other and enabling potential customers to broaden their search space (Jabr & Zheng, 2017). Hybrid filtering (HF). This RAT combines CF and CBF techniques by

integrating individual and community preferences , which **may** produce **better decision quality** 32 **than either pure** CF **or pure**

CBF (Xiao & Benbasat, 2007, 2014b). A typical commercial example is Netflix, which recommends movies that share characteristics with films a customer has previously watched and rated highly (content-based filtering 86

) and recommends movies

by comparing the watching and searching patterns of similar customers (collaborative filtering 86

) (Gomez-Uribe & Hunt, 2015). The REA enables an explicit disclosure and explanation of the three primary RATs and thus allows users to understand the inner workings of an RA's recommendation mechanisms. Based on CLT, we theorize that an actualized REA influences perceived effectiveness, perceived transparency, and perceived integrity. An REA is actualized when RA users employ it

to achieve immediate concrete outcomes that support their goals 2

, such as making ideal product choices based on relevant knowledge of the mechanisms by which the product is recommended. In our study, the UI-disclosure and -explanation features are the artifacts (Figure 2) that provide users with information regarding the RAT an RA uses to recommend 108 products. 2.4.2. Bias-Explaining Affordance We define the BEA as

the extent to which a user perceives that an RA provides an opportunity to understand the 2

inner workings of biased RAs. In the context of e-commerce product RAs,

biased recommendations are produced **based on business** rules **that balance the gains of vendors and the experience of users** 84

(Chau et al., 2013). Biases arise

when an RA systematically favors a small subset **of items over other items irrespective of users** ' 48 interests and **preferences (Krishnasamy et al**

., 2016) and acts contrary to users’ best interests (Xiao & Benbasat, 2018). Biased RAs commonly involve product sponsorship (Wang & Wang, 2019; Wang et al., 2018a), information about warehouse-stock levels, commissions from vendors, and vendors’ promotion strategies (Chau et al., 2013). Building on Wang and Wang (2019) and Wang et al. (2018a), our study focuses on the affordance of unveiling and explaining sponsored recommendations. In our research context, sponsored recommendation is the commercial practice in which a biased AI- powered RA recommends and displays sponsored products to consumers before recommending nonsponsored products. Wang and Wang (2019) pointed out that in the context of biased RAs, the influences of sponsorship disclosure remain unclear and the theoretical understanding of these biased RAs’ effects is limited. For instance, some studies have suggested that disclosure improves RA transparency, which may in turn increase perceived RA integrity (e.g., Wang & Benbasat, 2007; Wang & Wang, 2019),

because the disclosure and explanation **may be interpreted as a signal of honesty** 48

and integrity (Abendroth & Heyman, 2013). However, other studies have found that sponsorship disclosure may undermine source credibility (Jansen et al., 2007) and induce potential negative responses

once users are informed of the use of sponsorship practices 1

(Wang & Wang, 2019; Wang et al., 2018a). Building on the work of Wang and Benbasat (2007) and Wang and Wang (2019), we examine this controversy in the AI-powered RA context using an affordance lens. Specifically, the BEA enables the explicit disclosure and explaining of sponsored recommendations and thus allows users to understand the inner workings

of a biased RA . Drawing on **the** theoretical perspectives **of knowledge-based trust** 48

and 109 psychological contract violation (PCV), we theorize that an actualized BEA affects perceived transparency, perceived integrity, and perceived deceptiveness. A BEA is actualized when RA users employ it

to achieve immediate concrete outcomes that support their goals 2

, such as making informed purchase decisions based on sponsorship-disclosure information. Figure 2 depicts the UI artifacts of bias-disclosure and -explanation features, which provide users with information about sponsored recommendations in a biased RA. 2.5. Theory of Social Responses to Computers To examine the effects of user perceptions of RAs on trust and distrust, this study draws on

the theory of social responses to computers (TSRC), **developed by Reeves and Nass** (1996). **The** 58

TSRC posits that consumers treat computer-based agents

as social actors and apply social rules to them 33

in the process of forming social relationships that involve trust. Empirical studies have shown that even tech-savvy people perceive technological artifacts as possessing human characteristics such as motivation, integrity, and personality (Reeves & Nass, 1996). A variety of studies have extended the TSRC to RAs (Komiak & Benbasat, 2006), embodied conversational agents (Cassell & Bickmore, 2000), crowdfunding platforms (Mejia et al., 2019), and other abstract technical systems (Muir & Moray, 1996). The evidence from these studies supports the conclusion that users assign human characteristics to technological artifacts and respond to them socially (Wang & Benbasat, 2005; Xiao & Benbasat, 2007). Moreover, Wang and Benbasat (2005) pointed out that certain

components of trust in humans and in technological artifacts do not differ significantly 33

. As with trust in humans, users' beliefs about a technology's ability to deliver through its promised objective characteristics are reflected in their assessments of the technology's attributes (McKnight et al., 2011). Specifically, McKnight et al. (2011) claimed that the three

trusting beliefs in humans' **competence, benevolence, and integrity** are mirrored by **the** beliefs in **a** 103

technology's functionality, helpfulness, and reliability, respectively. These trusting beliefs will apply to the RA affordances provided by technology artifacts. Drawing on the TSRC, we include both trust and distrust in the conceptual model (Figure 2) to investigate their mediating effects using a two-process view of trust and distrust building 1

. 110 2.6. Two-Process View of Trust and Distrust Building

According to the two-process view, trust building and distrust building are distinct **processes** that **can be** influenced **by the same antecedent in different ways** 9

(Komiak & Benbasat, 2008). This is consistent with Lewicki et al.'s (1998a)

two-construct view , which posits **that trust and distrust can** coexist **in an inconsistent state** , in which **a combination of** low **trust and low distrust or a combination of** high **trust and high distrust** 9

can occur. The two-process view posits that

trust and distrust are not just **the opposite ends of a single continuum** (e.g., **Komiak & Benbasat, 2008; Lewicki et al** 1

., 1998a), because

trust is a positively valenced **belief and an** anticipation **of the** beneficial **conduct of others** , whereas **distrust is a** negatively valenced **belief and an** anticipation **of others' injurious conduct** 1

(Wang et al., 2018a). NeuroIS research has shown that

trust and distrust activate different areas of the brain and have **different effects** , which explains **why they are** distinct **constructs associated with different neurological processes** 162

(

Dimoka, 2010). Komiak and Benbasat (2008) adapted **the** two-process view **to the** RA context **and** 272

suggested that trust and distrust processes can coexist and act independently for two major reasons: (1) the multifaceted relationships between the customer and the RA (e.g., the RA user's double role as a customer and an IT user and the RA's double role as a social actor and a tool) enable the customer to hold simultaneously different views of the RA; (2)

the inconsistency between individual trust- and distrust-building processes is not resolved quickly, and 9

thus users cannot decide whether the RA is trustworthy overall while interpreting information about it. To be consistent with the insights these theoretical perspectives provide,

we treat trust and distrust as separate constructs and examine both **the** antecedents and consequences **of** 242

trust and distrust in our model

to gain a better understanding of the effects of the 284

REA and BEA and their perceived RA outcomes. 3. Research Model and Hypothesis Development We propose an integrated research model (Figure 2) that explains how UI artifacts provide both the REA and BEA, which, when actualized, can influence users' perceptions of an RA (i.e., perceived effectiveness, perceived transparency, perceived integrity, and perceived deceptiveness). We predict that these 111 perceptions will influence users' PDC with the RA through the mediating effects of trust and distrust. Figure 2. Proposed Research Model 3.1. RA Design Artifacts and Explaining Affordances IT artifacts are defined as the "application of IT to enable or support some task(s) embedded within a structure(s) that itself is embedded within a context(s)" (Benbasat & Zmud, 2003, p. 186). Although explaining affordances can originate from many different RA artifacts, our study focuses on the UI artifacts that explicitly disclose and explain RATs and sponsored-recommendation bias in an RA.

A core theoretical premise of this study is that UI artifacts **can be** manipulated **to affect** user 47 perceptions **and subsequent**

behaviors. Previous studies have shown that UIs can act as a stimulus and

directly affect cognitive processing and subsequent persuasion (e.g., **Lowry et al**., 2017; **Lowry** 47

et al., 2014; Vance et al., 2015). Because the RAT-disclosure artifact explicitly provides information and cues about the three major RATs (i.e., CBF, CF, and HF), we predict that it will enhance the user's perceived REA. Similarly, the sponsored-recommendation-disclosure artifact explicitly reveals the inner workings of a biased RA, and users will likely have an increased awareness of the existence of the BEA. Therefore, we hypothesize that: H1a. UI artifacts that manipulate the RAT disclosure will increase the perceived REA. H1b. UI artifacts that manipulate the sponsored-recommendation disclosure will increase the perceived BEA. 3.2. The Recommendation-Algorithm-Type-Explaining Affordance and Perceived Effectiveness Effectiveness, by definition, depends strongly on the accuracy of the RA (Tintarev & Masthoff, 2011). In the context of e-commerce RAs, an effective RA provides high-quality recommendations and helps users make better-informed purchase decisions (Aggarwal & Vaidyanathan, 2003b).

Aggarwal and Vaidyanathan 112 (**2003b**) argued that **perceived effectiveness** can be **measured by user perceptions of the** overall **quality of recommendations, satisfaction with the** results, **and intention to** 32

accept the recommendations. Drawing on Tintarev and Masthoff (2011), we posit that an actualized REA will help users feel more comfortable with the underlying recommendation mechanisms and better evaluate the quality of suggested items, which will in turn increase the likelihood that they will discard irrelevant recommended items and recognize useful ones. It has been found that well-designed explanation artifacts allow customers to form a clear mental model of the RA and judge the advice quality by understanding the process by which the RA recommends the items and

the extent to which the recommended items fit **their** needs and **preferences** 174

(Wang & Benbasat, 2007, 2016). In addition to convincing users of the quality of its advice, the disclosure and explanation designs reduce the effort required to make an RA-assisted decision. Both effects are expected to increase customers' perceived effectiveness, which leads to higher trust in the RA's competence (Wang & Benbasat, 2005; Xiao & Benbasat, 2007) and higher customer satisfaction (Tintarev & Masthoff, 2012). Thus, we hypothesize that: H2. REA will increase the perceived effectiveness of an RA. 3.3. The Bias-Explaining Affordance and Perceived Deceptiveness Adapting Xiao and Benbasat's (2011) definition of perceived deceptiveness in e-commerce websites to the RA context, we define this construct as

the extent to which a user believes that an 2

RA is deceptive in terms of the content, presentation, and generation of recommended information. According to Xiao and Benbasat (2011), perceived deceptiveness often results from the deceptive information practices of e-commerce merchants or from the recognition of cues suggesting deceptive information practices. It is triggered by a negatively valenced violation of a user's preconceived expectations and is an outcome of the user's deception-detection process (Xiao & Benbasat, 2011). In the context of sponsored recommendations in RAs, perceived deceptiveness may be triggered when users detect recommendation bias

in the absence of a transparent **disclosure of** sponsorships, **especially for the biases** users **can easily** 48

detect. During the early stages of their interaction with an RA, users may not notice a recommendation bias for sponsored products, 113 but they may gain the ability to detect it after repeated use of the RA (Wang & Wang, 2019). Once triggered, a user's perception of deception usually

exists in a state of uncertainty regarding **the** RA's **honesty** ; hence, **the** 179

user is likely to seek additional evidence before arriving at a firm conviction about the RA's truthfulness (Xiao & Tan, 2012). We argue that at this crucial moment of conviction formation, an actualized BEA that discloses and explains the sponsored recommendation as a legitimate business practice gives users the evidence needed to mitigate their perceived deceptiveness of the RA's recommendations. Therefore, we hypothesize that: H3. BEA will decrease the perceived deceptiveness of an RA. 3.4. Explaining Affordance and Perceived Transparency Transparency refers to revealing the work performed behind a service or system, which increases users' perceptions of trust and effort (Buell & Norton, 2011; Mejia et al., 2019). In the context of AI-powered e- commerce recommendation technology, an RA is perceived as transparent when users understand the inner workings of the black box's product recommendations and the underlying characteristics and motives that drive its behaviors (Wang & Benbasat, 2016). The disclosure and explanation of the inner workings of the system can provide transparency, exposing the reasoning and process behind a recommendation (Tintarev & Masthoff, 2012). Prior studies have provided empirical support for

the general principle of “honesty is the best policy” **and** confirmed **the positive effect of disclosure** and explanation **through the** RA’s **increased transparency** 48

(e.g., Wang & Benbasat, 2016; Wang & Wang, 2019). In our research model, when an RA provides disclosures and explanations regarding RAT and sponsored recommendation, the RA becomes profoundly transparent with its recommendation algorithms and biases toward sponsored products, and its behavior becomes more predictable. Therefore, we posit that both an actualized REA and an actualized BEA will reduce information asymmetry and enhance system visibility, thereby increasing perceived transparency. Thus, we hypothesize that: H4a. The REA will increase the perceived transparency of an RA. H4b. The BEA will increase the perceived transparency of an RA. 114 3.5. Explaining Affordance and Perceived Integrity Perceived integrity

is the perception that an RA adheres to a set of generally accepted **principles** such as **honesty** , trustworthiness, sincerity, **and** promise **keeping** 55

(McKnight et al., 2002; Wang & Benbasat, 2007; Wang & Wang, 2019). According to the TSRC, consumers treat computer-based agents

as social actors and apply social rules to them 33

in the process of forming social relationships that involve trust (Reeves & Nass, 1996). Anthropomorphism is the ascription of human properties to technological artifacts, and anthropomorphic behaviors toward a system guide people develop their communications and interactions with the technology (Johnson, 1994; Marakas et al., 2000). Consumers

respond socially to technological artifacts and perceive that they possess human characteristics such as integrity, **motivation, and personality** 33

(Wang & Benbasat, 2005). An RA is deemed to exhibit high integrity when a user perceives that it has a strong sense of honesty, sincerity, candidness, and objectivity. With people, integrity refers to

the trustee’s honesty and promise keeping (McKnight et al., 2002 245

). With technology, integrity takes the form of reliability, which reflects

the belief that the technology in question **will** operate **consistently, properly** , and predictably (**McKnight et al., 2011). The** 100

REA helps users understand the inner workings of the system and thus increases the perceived consistency and predictability of the system. In addition, from the knowledge-based trust perspective, providing disclosures and explanations regarding an RA's recommendation algorithms could bridge the knowledge gap caused by information asymmetry and indicate that the RA is candid and does not hide information from users, which may in turn enhance perceived integrity (Wang & Benbasat, 2007). Therefore, we hypothesize that: H5a. The REA will increase the perceived integrity of an RA. Disclosures and explanations of sponsored recommendations are more controversial, because they may undermine source credibility and hamper system performance (Jansen et al., 2007) but may be interpreted in the meantime as a signal of honesty (Abendroth & Heyman, 2013). Users may have mixed responses to biased RAs, because they benefit users by offering

organic recommendations while promoting sponsored **products (Animesh et al., 2010** 48

). Acting on this perspective, Wang and Wang (2019) applied the PCV theory 115 and

a contingency approach to examine **a condition under which sponsorship disclosure by a biased RA is effective in** 48

increasing a user's perceived integrity via reducing perceived PCV. Their findings revealed that (1) sponsorship disclosure

can enhance perceived integrity via reduced perceived PCV only for users with high prior knowledge **but not for those with low prior knowledge** 48

and (2)

sponsorship disclosure enhances users' perceived transparency of a biased RA, which in turn strengthens **perceived RA integrity** 31

(Wang & Wang, 2019). Drawing on these theoretical mechanisms, we hypothesize that the BEA, when actualized in the context of a disclosure of a legitimate sponsored-recommendation business practice, will have an overall positive effect on perceived integrity. H5b. The BEA will increase the perceived integrity of an RA. 3.6. User Perceptions and Trust/Distrust Our model adopts

the two-process view , which posits that **trust building and distrust building are** distinct **processes** and **can be affected by the same antecedent in different ways** 9

(Komiak & Benbasat, 2008). According to the two-process view,

trust and distrust are not simply the opposite ends of a single continuum (e.g., **Komiak & Benbasat, 2008; Lewicki et al** 1

., 1998a), because

trust is a positively valenced **belief and an expectation of the** beneficial **conduct of others** , whereas **distrust is a** negatively valenced **belief and an expectation of others' injurious conduct** 1

(Wang et al., 2018a). An RA's explaining affordance aims to improve user perceptions of the RA, which in turn support the building of trusting beliefs and diminish distrusting beliefs. Trusting beliefs are the truster's confident perceptions

that the trustee has attributes that are beneficial to the truster (McKnight et al., 2002 100

). Trust in

an RA involves **one's perceptions** of **the RA's competence** , integrity, **and** 55

benevolence (Komiak & Benbasat, 2006). Competence belief is the

perception that an RA has the ability, skills, and expertise to effectively 55 address a user’s needs;

integrity belief is the perception that an RA adheres to principles 55

that are generally accepted by users, such as honesty and promise keeping; and

benevolence belief is the perception that an RA cares about the user **and** 58

is motivated to act in the user’s interests (Komiak &

Benbasat, 2006; McKnight et al., 2002; Wang & Benbasat, 2007 30

). McKnight et al. 116 (2011) suggested that trust in a specific technology is reflected in three highly similar but slightly different trusting beliefs: (1) functionality, that is, whether an individual expects a technology to have the capacity to accomplish a required task; (2) helpfulness, that is, the help function of the technology itself by excluding mortal agency and volition; and (3) reliability, that is, an individual’s expectation that a technology will work predictably and consistently. These trusting beliefs can be integrated into a single trust construct; as a result, the construct can be included in many models and has greatly advanced trust research (

e.g., Fang et al., 2014; Gefen & Pavlou, 2012 54

; Tomlinson & Mayer, 2009). Our theoretical model adopts the single- construct approach and examines the influences of user perceptions (i.e., perceived effectiveness, perceived transparency, perceived integrity, and perceived deceptiveness) on trust. An effective e-commerce RA provides good recommendations and helps users make sound purchase decisions (Aggarwal & Vaidyanathan, 2003b; Tintarev & Masthoff, 2012). Higher perceived effectiveness of an RA will lead to a stronger competence belief in an RA. Perceived transparency is also critical in users’ development of trust in an RA, because it facilitates users’ conceptualization and comprehension of the system’s reasoning process (Wang & Benbasat, 2007), mitigates users’ concerns about goal incongruence, allows users to determine whether the recommendations truly match their requirements (Wang & Benbasat, 2016), relieves users of their worries about deceptive manipulations (Xiao & Tan, 2012), and presents to users as forthcoming with a low tendency to conceal information (Wang & Benbasat, 2007). Moreover, the black box nature of RA design gives rise to algorithm aversion (Mahmud et al., 2022), which refers to the phenomenon that people often choose humans in the decision-making process, even though evidence-based algorithms predict future results with greater precision than humans (Dietvorst

et al., 2015 ; Dietvorst **et al** ., 2018). Dietvorst **et al. (2015**) argued that **the** lack **of** 281

trust in algorithms and preference for humans are exacerbated, especially after users see an algorithm error. Berger et al. (2021) showed that transparently demonstrating a system's performance improvements over time can lower users' aversion toward an erring algorithm. In addition, Mahmud et al.'s (2022) systematic literature review on algorithm aversion indicated 117 that users often exhibit aversion because they lack access to an algorithm's rationale, as a result of which they trust it less, whereas users perceive an algorithm as more trustworthy when they receive a persuasive explanation of how the algorithm works. In summary, we expect that perceived transparency will enhance all three trusting beliefs in the RA. H6a. Perceived effectiveness will increase trust in an RA. H6b. Perceived transparency will increase trust in an RA. Perceived integrity reflects ethical principles, including perceived honesty, trustworthiness, sincerity, and promise keeping (McKnight et al., 2002; Wang & Benbasat, 2007; Wang & Wang, 2019), which are closely associated with trusting beliefs concerning integrity and benevolence. Mayer et al. (1995) pointed out that several theorists have identified perceived integrity (or similar constructs) as an antecedent to trust and have suggested that integrity is especially

important to the formation of trust early in the relationship 274

. Luo and Cook (2007) empirically validated perceived integrity as an antecedent to a consumer's trust in an online rating system. We posit that perceived integrity is equally applicable to the trust-building process in the context of AI-powered RAs. Hence, higher perceived integrity will lead to stronger trusting beliefs in the RA's integrity and benevolence. Conversely, perceived deceptiveness produces a bias in consumers' attitudes that leads them to become broadly distrustful and defensive (Darke & Ritchie, 2007). In the e- commerce context, Xiao and Benbasat (2011) proposed a two-dimensional typology of deception that delineates (1) three deception types (i.e., concealment, equivocation, and falsification) and (2) three deception techniques (i.e., manipulations of information content, presentation, and generation). These deception types and techniques, when perceived by consumers, will prime negative beliefs about the providers' truthfulness (Darke & Ritchie, 2007). Drawing on these theoretical perspectives, we posit that deceptive recommendation practices will decrease users' trusting beliefs in an RA. Therefore, we hypothesize that: H6c. Perceived integrity will increase trust in an RA. H6d. Perceived deceptiveness will decrease trust in an RA. 118 Rooted in goal and value incongruence, distrusting beliefs are more emotionally charged than trusting beliefs and involve a reluctance

to become vulnerable to trustee , stemming from a **belief that** they **will not perform the** 183
desired behavior (**McKnight & Chervany** , 2001b; **McKnight et al**

., 2002; Moody et al., 2017). McKnight and Chervany (2001a) compared

trust and distrust to two elephants: trust is like the docile zoo elephant munching on hay , whereas **distrust is like the** "raging wild bull elephant" **protecting the herd from attack** 80

(p. 885).

Although distrust is conceptually distinct from trust, it can **also be examined** 84

in terms of the three trust dimensions (i.e., competence, integrity,

and benevolence), because both trust and distrust involve **interpersonal relationships among humans or** the relationship **between a human and a technology** 169

(Chau et al., 2013). Prior research has suggested that distrusting beliefs can be operationalized using three dimensions whose valence is the opposite of that

of the trust dimensions: **incompetence** , deceit, **and** malevolence (**McKnight & Choudhury, 2006; McKnight et al., 2004** 26

; Moody et al., 2017). In the context of AI-powered RAs, perceived incompetence is one's belief that an RA lacks the ability to perform desired recommendation tasks; perceived deceit is one's belief that an RA is dishonest and predisposed to provide false information; and perceived malevolence is one's belief that an RA has malicious intentions that could compromise one's welfare. Our theoretical model proposes a single distrust construct and examines the influences of user perceptions on distrust. We predict that the three positive perceptions (perceived effectiveness, perceived transparency, and perceived integrity) will mitigate all three distrust dimensions (incompetence, deceit, and malevolence). We predict that perceived deceptiveness will increase the deceit and malevolence dimensions of distrust. Therefore, we hypothesize that: H7a. Perceived effectiveness will decrease distrust in an RA. H7b. Perceived transparency will decrease distrust in an RA. H7c. Perceived integrity will decrease distrust in an RA. H7d. Perceived deceptiveness will increase distrust in an RA. Moreover, trust is a positively valenced belief and an expectation that others will behave beneficially, whereas distrust is a negatively valenced belief and an expectation that others will behave injuriously (Wang 119 et al., 2018a). Distrust is accompanied by feelings of worry, fear, suspicion, panic, paranoia, anger, and

concern, in contrast to the calm and **secure feelings that accompany trust**	80

(Lewicki et al., 1998a; McKnight et al., 2004). The negatively valenced beliefs arise for a good reason; a breach of trust of some sort often takes place before one develops high levels of distrust (McKnight & Choudhury, 2006). A breach of trust (e.g., deceptiveness) causes a negative emotional reaction that is strongly associated with the person's distrust, and

the emotional intensity of distrust distinguishes it from trust	80

(McKnight & Choudhury, 2006; McKnight et al., 2004). Once a user has developed distrust in an RA, improvements in perceptions will take a longer process to pacify the "raging wild bull elephant" and thus will have a lesser influence on distrust than on trust. Drawing on these perspectives, we contend that positive perceptions of an RA (i.e., perceived effectiveness, perceived transparency, and perceived integrity) will have a stronger influence on trust than on distrust, whereas negative perceptions (i.e., perceived deceptiveness) will have a stronger influence on distrust than on trust. 3.7. Trust/Distrust and Perceived Digital Companionship In our research context, PDC is a combination of affection, attachment, commitment, and intimacy between users and AI-powered RAs. The metaphor of digital companionship draws on theoretical concepts of the constitutive characteristics and qualities of human relationships (Carolus et al., 2018) and Hatfield et al.'s (2008) general definition of companionship. This metaphor also aligns with the TSRC, which posits that users treat computer-based

agents as social actors to **form social relationships that involve trust**	33

(Reeves & Nass, 1996). Benyon and Mival (2010) suggested that simple interactions between humans and intelligent systems will evolve into a sustained relationship, which could be either positive or negative, just as in human relationships. Because users' intentions for short-term use of RAs have been extensively studied (e.g., Benbasat & Wang, 2005; Komiak & Benbasat, 2006;

Qiu & Benbasat, 2009; Wang & Benbasat , 2009; **Xu et al** ., 2014; Young Eun & **Benbasat**	152

, 2011), our study focuses on the tension that arises from the symbiotic relationship between users and intelligent RAs. We argue that this tension plays a key role in users' sustained use of these highly personalized systems. 120

In e-commerce, trust is a **prerequisite for customer-relationship building** 161

(Papadopoulou et al., 2001) and the cornerstone of successful and lasting customer relationships, because it

determines the customer's future behavior and loyalty toward **the business (Berry** 161

, 2004). Carolus et al. (2018) empirically demonstrated that digital companionship can be characterized on the basis of basic psychological constituents and outcomes of human relationships. Through repeated interactions with an RA, users can respond socially to interactions with RA artifacts, and they do perceive the artifacts' properties as humanlike (Wang & Benbasat, 2007). Therefore, we expect positively valenced beliefs (trust) to strengthen users' sense of companionship with an RA and negatively valenced beliefs (distrust) to weaken it. Therefore, we hypothesize that: H8. Trust will increase PDC with an RA. H9. Distrust will decrease PDC with an RA. 4. Methodology and Design 4.1.

Factorial Survey Method The FSM **is a specialized form of the scenario method** 47

(Vance et al., 2015),

which uses vignettes to "present subjects with written descriptions of realistic situations and then request responses on a number of rating scales that measure the dependent variables of interest" (**Trevino, 1992, pp. 127-128**). Recent **IS** 47

research has adapted the FSM for the study of graphical IT-design artifacts (e.g., Lowry et al., 2017; Vance et al., 2015).

To the best of our knowledge , our study **is the first to use the** FSM **to** 130

simulate various graphical disclosure and explanation UI artifacts of RAT and recommendation bias in the context of commercial AI- driven RAs. We chose Amazon's product-recommendation page, which is powered by its AI recommendation engine. In contrast to the experimental RAs used by prior RA studies, our study's novel adaptation of the FSM allowed us to investigate the impact of the explaining affordance provided by the UI-design artifacts of a large commercial RA and the differential responses of real RA users (instead of students) to the same hypothetical text and visual cues (Wallander, 2009). According to Vance et al. (2015),

the factorial survey is neither an experiment nor a traditional survey ; 121 rather, it **draws on** 47

the best qualities of both to provide a truly unique method. It also allows researchers to test a vast number of manipulations while avoiding the otherwise expected multicollinearity issues (Lowry et al., 2017; Vance et al., 2015). Similar to experiments, dimensions or factors of theoretical interest drive the design of factorial surveys, in which each dimension consists of multiple levels that are analogous to experimental treatments (Vance et al., 2015). The FSM allows researchers

to simultaneously manipulate a number of factors using contextualized 56

vignettes with different levels of manipulations of the exogenous variables (Jasso, 2006; Martin, 2012). Vance et al. (2015) explained that

these dimensions and levels are incorporated into the vignettes 47

, which are then used to obtain

a full factorial of all the **combinations of levels and dimensions** 47

. The orthogonality achieved by the full factorial allowed us to clearly distinguish between the effects of the manipulations of disclosure and explanation UI artifacts. The main components of factorial surveys are vignettes (Wallander, 2009), which are also referred to as the factorial objects judged by the respondents (Rossi & Nock, 1982). Atzmüller and Steiner (2010, p. 128) defined the vignette as “a short, carefully constructed description of a person, object, or situation, representing a systematic combination of characteristics.”

Vignettes represent different combinations of levels (values) of various dimensions (variables) (Wallander, 2009) and **are** 234

constructed in such a way that the respondent is presented with concrete and

relatively detailed information pertaining to **the independent variables of interest (Trevino, 1992** 264

). IS studies of user perceptions of technology, trust, and behaviors commonly use vignettes (e.g., Cummings & Dennis, 2018; Dennis et al., 2012; Lowry et al., 2017). They allow researchers to place all the respondents in the same scenario, with the desired manipulation as the only change needed, which improves researchers' control (Cummings & Dennis, 2018). As a result of this control, the participants' perceptions are less contaminated than they are in traditional experiments (Cummings & Dennis, 2018). Meta-analyses have provided evidence that participants respond quite similarly whether they are presented with a hypothetical situation in a traditional lab experiment or a hypothetical situation based on a vignette (Dennis

et al., 2012). As Vance **et al. (2015) and** Lowry **et al** 309

. 122 (2017) demonstrated, an FSM that incorporates graphical vignettes is an appropriate approach for UI artifacts, because it enables an

evidence-based design of IT artifacts that maximizes contextual realism and **experimental control** 56

. To adapt the FSM to the RA research context, we followed their approach and

used a combination of graphical and textual treatments with hypothetical 56

RAT- and bias-disclosure vignettes. 4.2. Adaptation of the Factorial Survey Method to Our Research Context Following Vance et al. (2015) and Lowry et al. (2017), we used Amazon, the world's leading e-commerce platform, as an empirical context in which to illustrate how the explaining affordance provided by UI- disclosure artifacts can influence user evaluations and perceptions of an RA. A McKinsey report7 showed that 35% of what consumers purchase on Amazon is driven by Amazon's AI-powered recommendation engine, which utilizes both content-based and collaborative filtering. 8 Using Amazon's product- recommendation page as a template (Figure 3), we developed two sets of graphical UI-design artifacts, which corresponded to the effects of RAT disclosure and bias disclosure, respectively. Table 1 presents these hypothetical UI artifacts, which are combined and superimposed on a screenshot of the Amazon recommendation page to create a factorial of eight unique graphical vignettes (4 x 2). Our design of the UI artifacts provided easily recognizable icons of sponsored recommendations (Sponsored Rec) and recommendation methods (Rec Blackbox) and displayed relevant explanations in a pop-up message box when a user hovered the mouse (with a finger indication) over the icon sets. 7

https://www.mckinsey.com/industries/retail/our-insights/how-retailers-can-keep-up-with-consumers **8**	41

https://aws.amazon.com/blogs/media/whats-new-in	175

-recommender-systems/ 123 Table 1. Graphical and Textual Treatments Effects Graphical UI Artifacts Textual Information RAT disclosure 1) Without (w/o) RAT disclosure There is no indication of the recommendation method used. 2) With (w) RAT - CBF disclosure Our AI-powered recommendation agent recommends these products using content-based filtering (CBF) techniques, which are based on your product preferences and recent purchases. 3) With (w) RAT - CF disclosure Our AI-powered recommendation agent recommends these products using collaborative filtering (CF) techniques, which are based on what other similar customers have recently bought and liked. 4) With (w) RAT - HF disclosure Our AI-powered recommendation agent recommends these products using both content- based and collaborative filtering techniques (hybrid), which are based on your product preferences and recent purchases as well as what other similar customers have recently bought and liked. Bias disclosure 1) Without (w/o) disclosure There is no indication of sponsored recommendations. 2) With (w) disclosure Our business sponsors have paid for these recommendations displayed at the top of the recommendation list, and the system shows a "Sponsored Rec (SR)" label next to the product. These sponsored products are recommended to you based on their relevance to your preferences. However, other non-sponsored products not appearing at the top of the list may better fit your preferences and needs. 124 Figure 3 illustrates the vignette design and all the combinations. Figure 4 provides a sample vignette with the callout labels that indicated the presence or absence of each UI-disclosure artifact and helped the respondents distinguish between different vignettes (see Appendix C for all eight vignettes). The graphical UI artifacts used Amazon's color scheme, whereas the textual information drew on both prior literature (Balabanović & Shoham, 1997; Xiao & Benbasat, 2007) and information on Amazon's website.9 This design strengthened the contextual

realism of and the **personal connection to the factorial survey**	47

(Vance et al., 2015) and allowed us to more effectively test likely realistic responses (Lowry et al., 2017), increasing the study's ecological validity. Each survey respondent randomly received a set of two vignettes from the eight possible combinations and provided a response to each vignette.

Apart from manipulating the exogenous factors related to the	4

RAT- and bias-disclosure artifacts, we built on Wang and Wang (2019) and included a manipulation of respondents' prior knowledge of RATs and recommendation bias (see Appendix B). 9

https://aws.amazon.com/blogs/media/whats-new-in 175

-recommender-systems/ 125 Figure 3. Vignette Design with Graphical and Textual Treatments Figure 4. Sample Vignette (Sponsored-Recommendation Disclosure + CF Disclosure) 4.3. Experimental Procedures and Survey Instrument This study followed Vance et al.'s (2015) multiphase experimental approach, which includes prevignette measures, prior knowledge manipulation, random assignment of graphical vignettes, and postvignette 126 measures. Figure 5 depicts the timeline of these elements. Figure 5. Multiphase Experimental Approach, Adapted from Vance et al. (2015) In phase 1, respondents answered screening questions to ensure that (1) they were 18 years of age or older; (2) they were Amazon customers residing in the United States who had at least one year of experience using the website; (3) they were familiar with Amazon's product-recommendation page; and (4) they had recently purchased products suggested by Amazon's recommendation engine. After passing the screening questions, the respondents answered demographic and background questions regarding gender, race, education, employment, income, overall IT proficiency, trust propensity, attitude toward AI, and experience with RAs (see Appendix Table D28). The resulting demographic and psychometric data were used as control variables. For phase 2, we followed Wang and Wang (2019) and manipulated the respondents' prior knowledge by showing (or not showing) them a fictitious Businessweek article. The article synthesized materials from prior literature (e.g., Balabanović & Shoham, 1997; Wang & Wang, 2019; Wang et al., 2018a; Xiao & Benbasat, 2007) and provided information about the three major RATs (e.g., CBF, CF, and HF) and the sponsored-recommendation practice used by RAs (see Appendix B). We enforced a Qualtrics timer control to prompt the respondents assigned to the "with prior knowledge" group to read the article carefully. In addition, we designed a quiz with attention-check questions to ensure that the respondents 127 understood the content provided to them. A three-strike rule was implemented to filter out users who failed to pay close attention to the article's content. In phase 3, after being given further instructions, the respondents were randomly provided with graphical vignettes and assigned to one of the eight conditions. They were asked to carefully evaluate the disclosure-design features depicted in the vignette for the recommendation page. Follow-up attention-check questions were used to ensure that the respondents paid attention to whether a disclosure design was presented (i.e., yes or no) and to which type of disclosure design (CBF, CF, or HF) was presented. In phase 4, the respondents were asked to respond to items in a postvignette survey (Appendix Table A2) that assessed the research constructs. To ensure

the validity and reliability of the **scales** , we adapted all **the measurement items (with** 288

the exception of those for REA, BEA, and PDC) from previously validated scales to fit the context of AI- powered RA research. The research model's key

constructs were measured with multiple items using 7- **point Likert-type** 279

scales, with the endpoints labeled “strongly disagree” and “strongly agree.” We adapted Chan et al.'s (2019) wordings for affordance measurements and generated candidate items for the REA and BEA, because there are no existing scales for these explaining affordances. In addition to adapting the existing items for PDC, we developed several new items for this construct based on Hatfield et al. (2008) and Lee et al.’s (2017) definition of companionship. To ensure content validity, we submitted the instrument to a panel of business information technology doctoral students to obtain their feedback on the appropriateness of these candidate items, which we took into consideration while preparing the final version of the online survey, to be used for the FSM. 4.4. Data Collection We developed an online survey using

Qualtrics and collected data via the **Amazon Mechanical Turk (MTurk** 333

) crowdsourcing platform. Each respondent received a unique alphanumerical reward code at the end of the survey, which was entered into MTurk to verify completion for a monetary reward of $2.00. The Qualtrics survey engine allowed us to implement sophisticated block randomization and content checks to operationalize the factorial survey using graphical vignettes. The use of MTurk was appropriate, because 128 RAs are customer-facing applications and recent research has confirmed that in the context of consumer- oriented experiments,

MTurk samples are **of equal or better quality than professional** data **panels and student samples** 116

(Goodman &

Paolacci, 2017; Hauser & Schwarz, 2016 ; Horton **et al** ., 2011; Kees **et al** 116

., 2017). MTurk allowed us to reach a huge pool of real Amazon RA users with diverse demographic backgrounds,

which is virtually impossible using other data collection methods 2

. In our design and distribution of the online survey, we followed the guidelines suggested in the recent methodological literature on MTurk (Goodman et al., 2013; Lowry et al., 2016). We conducted two pilot studies to contextualize, improve, and validate our manipulations, procedures, and instrumentation (Lowry et al., 2017). In addition, we used these studies to optimize the survey's length and determine the appropriate amount of time to give the respondents to complete the study in order to avoid survey fatigue, which is a threat to validity and a potential source of bias. The pilot studies also helped us devise effective attention traps and content checks. The two studies included 46 and 93 adult subjects, respectively, who were recruited

via Amazon MTurk for a small fee for each subject 56

. According to Jasso (2006), the level of analysis in the FSM is

not the participant but the vignette itself. Therefore, **because each respondent rated** two **graphical vignettes, the n for the** pilot studies **was** 47

92 (n = 46 × 2 = 92) and 186 (n = 93 × 2 = 186), respectively. We performed an exploratory factor analysis, calculated the reliabilities and validities

of the survey items, and modified or dropped items **from the instrument as needed** 47

. Because the statistical analysis of the pilot data revealed an acceptable factor structure, we were able to proceed with the full data collection. For the full data collection, we recruited a total of 300 MTurk subjects from the US who submitted randomly generated reward codes through Qualtrics. Based on carefully implemented screening questions, attention-trap questions, and content-check questions regarding the manipulations, we discarded the invalid responses. Our data-cleaning process used multiple techniques (e.g., MTurk reward codes validation, survey duration, longstring, IRV, MD, evenodd) to ensure data quality, and it resulted in a final dataset of 289 responses (n = 289 × 2 = 578). 129 To prevent common-method bias (CMB) a priori, we adopted classic procedures, such as using well- established scales, improving scale items through pilot tests, using different scaling for some items, and randomizing the appearance of questions (

Podsakoff et al., 2003). We also employed **a** post hoc **marker variable** 98

approach, which has been proven to be a robust and rigorous technique for identifying CMB (Lindell & Whitney, 2001; Malhotra et al., 2006). We used "blue attitude" as the marker variable, which is virtually neutral to any theory, is theoretically unrelated to this study's constructs of interest, and has items that elicit cognitive processes similar to those of the constructs (Simmering et al., 2015). The study followed

the latest guidelines for preventing CMB and improving data quality in **MTurk panel studies**	4

(

Lowry et al., 2016; Mason & Suri, 2012; Paolacci et al., 2010	148

). 5. Data Analysis and Results We used IBM SPSS 26 and AMOS 27 to perform the statistical tests reported in this and subsequent sections. 5.1.

Manipulation Checks Prior to the data **analysis, we first** examined and confirmed **the effectiveness of the** three **manipulations**	56

using t-tests, as detailed in Appendix D. To test the effectiveness of RAT-disclosure manipulation, we compared the mean differences of all the constructs when RAT UI-disclosure artifact was absent and when it was present. Table D1 summarizes

the construct statistics and the results of the comparison of means	56

; all the p-values were under 0.05 and in the right direction, indicating that the RAT-disclosure manipulation was successful. Similarly, to test the effectiveness of the bias-disclosure manipulation, we compared the mean differences of all the constructs when bias UI-disclosure artifact was absent and when it was present. Table D2 summarizes

the construct statistics and the results of the comparison of means	56

; all the p-values were less than 0.05 and in the right direction, indicating that the bias-disclosure manipulation was successful. Lastly, we tested the effectiveness of the prior-knowledge manipulation by comparing the mean differences of all the constructs when the fictitious Businessweek article was absent and when it was present. All the mean differences were significant, with the exception of those for the BEA ($t = 1.322$, $p =$ 130 0.187) and perceived transparency ($t = 1.648$, $p = 0.100$), indicating that the prior-knowledge manipulation was mostly successful (see Table D3). In addition, we ran multivariate analyses of variance (MANOVAs) for the tests described above, which further confirmed the effectiveness of these manipulations. 5.2. Measurement Model

To test the measurement model , we examined **convergent and discriminant validity** 173

, reliability, multicollinearity, and CMB. Appendix D provides detailed results for all the tests. Table D5 shows that convergent validity was supported by sufficiently high standardized loadings (above 0.7) for most of our items and that all the

cross-loadings were lower than the loadings (Fornell & Larcker, 1981; Nunnally, 1978 236

). In addition, as Table D6 illustrates, all the

average variance extracted (AVE) values exceeded the suggested threshold of 0 .5, **and** all **the** 52

composite reliabilities (CRs) were greater than the AVEs (Hair et al., 2010), indicating adequate reliability in the current model. Because CR

does not assume that the loadings or error terms of the items are equal 15

, we chose CR as a more precise reliability measurement than Cronbach's alpha (Chin et al., 2003). To ensure sufficient discriminant validity, we examined

the square roots **of the AVEs** , which were **greater than all the interconstruct correlations, indicating** the convergent **validity** 145

of the scales. Moreover, because

the difference between the primary loading and each of the **other** loadings was **greater than 0.1** 94

(the loadings were greater than the nearest cross-loading in Table D5), discriminant validity was further supported (Lowry & Gaskin, 2014). We also checked for multicollinearity by calculating

the variable inflation factor (VIF) for the eight predicators **in the model**	111

(see Table D7). Research has recommended that the VIF be below 10 and has suggested that a VIF greater than or equal to 5 indicates

moderate multicollinearity and a VIF **greater than or equal to 10** indicates **severe multicollinearity**	94

(Hair et al., 2010; Larose, 2015). Our results showed that all the VIF values were less than 5 and that most of the correlations among variables were below 0.80 (Hair et al., 2010). Further, all the tolerance levels of the constructs were greater than 0.10 (Miles, 2014), suggesting

that multicollinearity was not an issue in our model . Finally, **we**	258

performed checks to establish a lack of CMB. Following Simmering et al. (2015), we used 131 blue attitude

as the marker variable; it is theoretically unrelated to	316

the proposed nomological network, and its items elicit cognitive processes similar to those of the study's constructs. As Table D8 shows, blue attitude had a nonsignificant effect on the dependent variable PDC ($\beta = -0.005$, $t = -0.112$, $p = 0.911$). Moreover,

Lindell and Whitney (2001) and Malhotra et al. (2006	328

) recommended that

a marker variable be used **to adjust the correlations among the principal constructs. In our case**	111

, high correlations

among any of the items of **principal constructs and** blue attitude **would indicate** 110

CMB, because the blue attitude construct should be weakly related to the other principal constructs. As Table D9 shows, the average correlation between blue attitude

and the other **principal constructs was** only 0.031 (**average p value = 0** 111

.551). Hence, we concluded that CMB was not a significant threat to our study. 5.3. Theoretical Model Test To test our theoretical model (Figure 2), we first performed

analyses of variance (ANOVAs) to test **the effects of** UI-design artifacts **on the** 66

REA and BEA (H1a–b) by comparing the "without disclosure" and "with disclosure" groups. Next, we used IBM AMOS 27,

a covariance-based structural equation modeling (CB-SEM) tool, to test the main structural **model** 6

(H2–H9). We then conducted additional tests using the SPSS mixed linear model to further validate the model. Lastly, we performed multiple serial mediation analyses using AMOS 27 and SPSS PROCESS Macro version 4.0 to test the indirect effects of UI- disclosure artifacts on PDC based on our proposed theoretical model. 5.3.1. Testing the Effects of UI-Design Artifacts We performed a univariate ANOVA to examine the direct effects of UI-design artifacts on perceived explaining affordances. Table 2 summarizes the ANOVA results. The respondents randomly assigned to the RAT-disclosure treatment group reported a stronger perceived REA ($F(1, 577) = 842.799$, $p < 0.05$). Similarly, the respondents randomly assigned to the bias-disclosure treatment group reported a stronger perceived BEA ($F(1, 577) = 651.028$, $p < 0.05$). Figure 6 depicts significant mean differences in the two explaining affordances between the "without disclosure" and "with disclosure" groups. This indicated that the UI artifacts that manipulated the RAT disclosure positively influenced the perceived REA whereas 132 those that manipulated the sponsored-recommendation disclosure positively influenced the perceived BEA. Therefore, H1a and H1b were supported. 5.3.2. Testing the

Structural Model To test the main structural **model, we used structural equation modeling (SEM** 228

), which can analyze all the paths in an integrated analysis consisting of measurements and structural models (Barclay et al., 1995; Bollen, 1989; Gefen et al., 2000). We used IBM AMOS 27, a CB-SEM tool, for the overall model analysis and testing of H2–H9.

The test of the structural model included estimates **of the path coefficients, which** represent **the strengths of the relationships** among **the** 191

latent constructs. We modeled all the constructs as reflective and measured them

using multiple indicators rather than summated scales . Table **2** . ANOVA **Results** 144

Hypothesis IV

DV Sum of Squares df Mean Square F p 322

H1a disclosure REA Within Groups 703.742 576 1.222 RAT Between Groups 1029.711 1 1029.711 842.799 0.000 Total 1733.452 577 H1b disclosure BEA Within Groups 1033.686 576 1.795 Bias Between Groups 1168.332 1 1168.332 651.028 0.000 Total 2202.018 577 BEA = bias explaining affordance; IV = independent variable; df = degrees of freedom; DV = dependent variable; RAT = recommendation algorithm type; REA = RAT explaining affordance Figure 6. Nondisclosure and Disclosure Mean Differences In CB-SEM analysis, the explanatory power of the structural model is examined through an analysis of

the R2 scores of the endogenous variables and structural path coefficients 247

. Figure 7 shows our structural model's explained variances and path coefficients. According to the literature on CB-SEM standards (Hu & Bentler, 1999; Kline, 2015), the common indices of the AMOS SEM indicated good model fit ($\chi^2$448 = 133 2085.312; χ^2/df = 4.65; CFI = 0.932; TLI = 0.924; RMSEA = .080). Figure 7. Structural Model Results The REA alone explained 26.2% of the variance in perceived effectiveness, whereas the BEA alone explained 14.3% of the variance in perceived deceptiveness (H2 and H3). The REA and BEA together explained 72.5%

of the variance in perceived transparency (H4a–b) **and** 28. **2% of the variance in perceived** 226 integrity (H5a–b). This indicated that the two explaining affordances

accounted for a significant amount of variance in user perceptions of **the** 331

RA. Together, perceived effectiveness, perceived transparency, perceived integrity, and perceived deceptiveness

explained 74% of the variance in trust (H6a–d) **and** 62% **of the variance in** 250

distrust (H7a–d). This indicated that the variances in trusting and distrusting beliefs were adequately explained by user perceptions of the RA. Trust and distrust together explained 30.3% of the variance in PDC (H8 and H9). Table 3 summarizes the hypothesis-testing results. The influences of the REA and BEA on user perceptions (H2–H5) were strongly supported ($p < 0.001$). With the exception of H6b ($p = 0.065$, just above the significance threshold), H6 was strongly supported;

the effects of perceived effectiveness, perceived integrity, **and perceived** deceptiveness **on** 301
trust (H6a, c, **and**

d, respectively) were highly significant ($p < 0.001$). Furthermore, H7d was strongly supported: perceived deceptiveness significantly increased distrust ($\beta = 0.755$, $p < 0.001$), whereas perceived integrity significantly decreased distrust (H7c, $\beta = -0.106$, $p < 0.05$). The effects of perceived effectiveness and perceived transparency on distrust were nonsignificant (p 134 > 0.05). As we expected, trust significantly increased PDC (H8, $\beta = 0.452$, $p < 0.001$), whereas distrust significantly decreased PDC (H9, $\beta = -0.178$, $p < 0.001$). Table 3. Hypothesis-Testing Results Hypothesis β SE CR p Supported? H2. REA → Perceived effectiveness 0.512 0.031 11.885 0.000 Yes H3. BEA → Perceived deceptiveness -0.379 0.031 -9.277 0.000 Yes H4a. REA→ Perceived transparency 0.788 0.030 22.901 0.000 Yes H4b. BEA → Perceived transparency 0.321 0.022 10.665 0.000 Yes H5a. REA → Perceived integrity 0.372 0.035 8.682 0.000 Yes H5b: BEA → Perceived integrity 0.379 0.028 8.958 0.000 Yes H6a: Perceived effectiveness → Trust 0.458 0.039 10.542 0.000 Yes H6b: Perceived transparency → Trust -0.061 0.024 -1.847 0.065 No H6c: Perceived integrity → Trust 0.568 0.040 11.289 0.000 Yes H6d: Perceived deceptiveness → Trust -0.328 0.029 -7.839 0.000 Yes H7a: Perceived effectiveness → Distrust -0.047 0.055 -1.053 0.292 No H7b: Perceived transparency → Distrust -0.034 0.037 -0.943 0.346 No H7c: Perceived integrity → Distrust -0.106 0.060 -1.983 0.047 Yes H7d: Perceived deceptiveness → Distrust 0.755 0.046 15.913 0.000 Yes H8: Trust → Perceived digital companionship 0.452 0.053 9.995 0.000 Yes H9: Distrust → Perceived digital companionship -0.178 0.042 -3.525 0.000 Yes BEA = bias explaining affordance; CR = critical ratio; RAT = recommendation algorithm type; REA = RAT explaining affordance; SE = standard error In addition, we compared subsample structural models for the “without bias” and “with bias” disclosure manipulations, respectively (see Appendix D). The results indicated that RAT disclosure significantly increased the influence of REA on perceived effectiveness, perceived transparency, and perceived integrity (Table D10 and Figure D5). Similarly, we compared subsample structural models for the “without disclosure” and “with disclosure” bias-disclosure manipulations. The results showed that bias disclosure significantly increased the BEA’s influence on perceived transparency, perceived integrity, and perceived deceptiveness (Table D11 and Figure D6). As Table D3 and Figure D3 show, prior knowledge manipulation did not affect the influence of the REA but increased the effect of BEA on user perceptions (Table D12 and Figure D7), suggesting that prior knowledge played a more salient role in bias disclosure than RAT disclosure.

This finding was **in line with prior** literature **on the** impact **of** 329

sponsorship disclosure (e.g., Wang & Wang, 2019; Wang et al., 2018a). 5.3.3. Additional Model Analysis with the Linear Mixed Model To further validate the model, we used the SPSS linear mixed model to break down the analysis further to 135 account for both the fixed and random effects embedded in our study’s FSM design. Known explanatory variables were associated with the fixed-effect parameters, whereas sampling procedures such as repeated measurement, which required the respondents to respond to two vignettes, were associated with random- effect parameters (Vance et al., 2013, 2015). Moreover, because the subjects were presented with two graphical vignettes, the observations were not independent, and correlation and nonindependence among survey responses were therefore present (Johnston et al., 2016; Mclean et al., 1991). The mixed-effects regressions allowed us to specify RA-specific fixed effects and user-specific random components (Dunn et al., 2020). The hypothesis-testing results (see Appendix Tables D13–D23) were highly consistent with the findings presented

in the previous section . Table 4 compares **the results of the** two **analysis** methods, both **of** 147

which provided strong empirical support for our research model. 5.3.4. Post Hoc Testing of Multiple Serial Mediations Our research model involved multiple serial mediations in which the effects of UI-disclosure artifacts on PDC were mediated by the explaining affordances, perceived effectiveness, perceived transparency, perceived integrity, perceived deceptiveness, trust, and distrust. To test these effects, we used IBM AMOS 27 and PROCESS Macro version 4.0 (using Model 6 with the “total effect models” and “standardized effects” options selected) to perform multiple serial mediations with 5,000 bootstrap samples to create 95% confidence intervals (Hayes, 2018). We chose bootstrapping in our mediation analysis for three reasons: (1) it can perform more accurate and powerful statistical mediation testing compared with traditional mediation tests; (2) it enables researchers to measure indirect effects directly rather than using a sequence of tests to merely infer their presence, as in the traditional method; and (3)

it does not assume that the mediation effect is normally distributed, which is 47 a substantial advantage over the Sobel test (Hayes, 2009, 2018). According to Hayes (2009, p. 412), “bootstrapping generates an empirical representation of the sampling distribution of the indirect effect by treating the obtained sample of size n as a representation of the population in miniature, one that is repeatedly resampled during analysis as a means 136 Table 4. Comparison of Hypothesis-Testing Results Hypothesis SEM & ANOVA Supported? LMM H1a. RAT disclosure → REA Yes* Yes H1b. Bias disclosure → BEA Yes* Yes H2. REA → Perceived effectiveness Yes Yes H3. BEA → Perceived deceptiveness Yes Yes H4a. REA → Perceived transparency Yes Yes H4b. BEA → Perceived transparency Yes Yes H5a. REA → Perceived integrity Yes Yes H5b: BEA → Perceived integrity Yes Yes H6a: Perceived effectiveness → Trust Yes Yes H6b: Perceived transparency → Trust No No H6c: Perceived integrity → Trust Yes Yes H6d: Perceived deceptiveness → Trust Yes Yes H7a: Perceived effectiveness → Distrust No No H7b: Perceived transparency → Distrust No No H7c: Perceived integrity → Distrust Yes Yes H7d: Perceived deceptiveness → Distrust Yes Yes H8: Trust → Perceived digital companionship Yes Yes H9: Distrust → Perceived digital companionship Yes Yes Note: *H1a and H1b in the first modeling testing used one-way ANOVA; ANOVA = analysis of variance; BEA = bias explaining affordance; RAT = recommendation algorithm type; LMM = linear mixed method; REA = RAT explaining affordance; SEM = structural equation modeling. of mimicking the original sampling process.” This

process involves resampling with a replacement from the obtained sample several thousand times	47

(Vance et al., 2015). Serial mediation analysis involves an analysis of

the indirect effect of an independent variable on a dependent variable through	232

a series of mediators (Hayes, 2018). Using the bootstrapping approach, we ran the analysis involving all indirect effects of UI-disclosure artifacts on PDC through serial mediators, including explaining affordances (i.e., REA, BEA), user perceptions (i.e., PE, PT, PI, PD), trust, and distrust. Appendix D (Figure D8 to Figure D19) provides detailed serial mediation diagrams with standardized path coefficients, and Table 5 summarizes the mediation test results. Because

none of the bias-corrected 95% confidence intervals contained **zero**	106

, the results showed significant indirect effects of RAT disclosure and UI-bias-disclosure artifacts on PDC through the affordance lens. In addition, both indirect effects were positive, suggesting that these UI-disclosure artifacts increased PDC through the serial mediations, as posited in our theoretical model (Figure 2). 137 5.3.5. Testing the Differential Effects of Recommendation-Algorithm Types The above tests addressed RQ1 and RQ2. For RQ3, our first goal was to examine whether users perceived the Table 5. Results of Serial Mediation Tests Serial Mediation Indirect Effect BootLL CI BootUL CI Zero included? Mediation significant? RAT Disclosure→REA→PE→TR→PDC 0.133 0.387 0.671 No Yes RAT

Disclosure→REA→PT→TR→PDC 0.142 0.526 0.893 No Yes RAT Disclosure→REA→PI→TR→PDC 0.138 0.440 0.765 No Yes RAT Disclosure→REA→PE→DISTR→PDC 0.104 0.138 0.269 No Yes RAT Disclosure→REA→PT→DISTR→PDC 0.157 0.328 0.585 No Yes RAT Disclosure→REA→PI→DISTR→PDC 0.125 0.152 0.331 No Yes Bias Disclosure→BEA→PT→TR→PDC 0.159 0.231 0.398 No Yes Bias Disclosure→BEA→PI→TR→PDC 0.161 0.324 0.576 No Yes Bias Disclosure→BEA→PD→TR→PDC 0.163 0.196 0.375 No Yes Bias Disclosure→BEA→PT→DISTR→PDC 0.206 0.100 0.218 No Yes Bias Disclosure→BEA→PI→DISTR→PDC 0.189 0.109 0.242 No Yes Bias Disclosure→BEA→PD→DISTR→PDC 0.220 0.112 0.257 No Yes BEA = bias explaining affordance; DISTR = distrust; PD = perceived deceptiveness; PDC = perceived digital companionship; PE = perceived effectiveness; PI = perceived integrity; PT = perceived transparency; REA = RAT (recommendation algorithm type) explaining affordance; TR = trust three RATs (i.e., CBF, CF, and HF) differently in terms of their effectiveness when their recommendation mechanisms were disclosed and explained. Because the three RATs differ only in their ways of making recommendations, we posited that they would not have differential effects on other variables. We ran a MANOVA to check whether RAT had significant between-subject effects on all the variables (see Appendix Table D23). The results showed that all the between-subject effects were nonsignificant, except for perceived effectiveness ($F(2, 441) = 3.223$, $p < 0.05$), indicating that users perceived the effectiveness of the three RATs differently. We then made a pairwise comparison of the perceived effectiveness means among respondents randomly assigned to the CBF, CF, and HF groups (see Appendix Table D24). The results indicated that users perceived collaborative filtering (CF) as the least effective of the three RATs (Figure 8), which was consistent with respondents' self-reported perceived RAT effectiveness after they read the fictitious Businessweek article that explained the three RATs (see Appendix Table D25).

To the best of our knowledge, our study is the first to 224

empirically test and report this interesting finding regarding users' perceived effectiveness of the three major RATs. 138 5.3.6. Testing the Moderation Effects of Prior Knowledge The second objective of RQ3 was to explore the impact of prior knowledge on our research model. The nature of this testing was exploratory for future research opportunities. We used Hayes' (2018, p. 612) PROCESS Macro model 92 to conduct multiple moderated mediation analyses (detailed reports are available upon request). We found two significant moderation effects in the serial moderated mediations, and the others were nonsignificant. Appendix D summarizes the key results. First, as Table D26 shows, prior knowledge negatively moderated (

β = -0 .204, **t = -2** .908, **p < 0** .05) **the** positive **effect of** perceived effectiveness **on** 45

trust in the serial mediation path REA→PE→TR→PDC. Figure 9 depicts the interaction effects between prior knowledge and perceived effectiveness. Figure 8. Effects of RAT Disclosure on Perceived Effectiveness 139 Figure 9. Interaction Effects of

Prior Knowledge × Perceived Effectiveness Second, as Table D27 shows, prior knowledge negatively moderated ($\beta = -0.334$, $t = -3.197$, $p < 0.05$) the positive effect of trust on PDC in the serial mediation path BEA→PD→TR→PDC. Figure 10 depicts the interaction effects between prior knowledge and trust. The results were consistent with the MANOVA manipulation check for prior knowledge (see Appendix Table D3), which indicated that prior knowledge reduced the means of the REA, the BEA, perceived effectiveness, perceived transparency, perceived integrity, trust, and PDC while increasing the means of perceived deceptiveness and distrust (Figure 11). This finding seemed to contradict those of prior empirical studies using experimental RAs (e.g., Wang & Wang, 2019). Although the information provided about the RAT and sponsored-recommendation bias was similar, respondents perceived the short and abbreviated disclosure through graphical UI artifacts much more positively than they did the article's detailed disclosure of the inner workings of the black box. A possible explanation for this interesting conundrum is that the disclosure of too much information about the AI black box could lead to counterproductive outcomes. Waldman (2020) pointed out that although many studies have contended

that computer -medicated **decision tools should be made as transparent as possible** 251

, others have indicated that excessive disclosure can erode trust. Research has shown that "users will not trust black box models, but they don't need – or even want – extremely high levels of transparency" (Hosanagar 140 & Jair, 2018, p. 4). Figure 10. Interaction Effects of Prior Knowledge × Trust Figure 11. Prior Knowledge Between-Group Effects (w/o vs. w) 6.00 5.00 4.00 Mean 3.00 2.00 1.00 0.00 REA BEA PE PT w/o Prior Knowledge PI PD TR DISTR PDC w Prior Knowledge BEA = bias-explaining affordance; DISTR = distrust; PD = perceived deceptiveness; PDC = perceived digital companionship; PE = perceived effectiveness; PI = perceived integrity; PT = perceived transparency; REA = recommendation-algorithm-type-explaining affordance; TR = trust. 5.3.7. Control Variables Following prior FSM studies (Lowry et al., 2017; Vance et al., 2013, 2015), in addition to demographics, we included several control variables based on respondents' experience with Amazon and its RA, as well 141 as their IT skills, trust propensity, and attitudes toward AI and AI bias (see Table A1 in Appendix A). As Appendix Table D29 reports, none of the control variables influenced PDC, except for respondents' years of experience with Amazon (

β = -0 .271, **p < 0.05) and** attitudes toward AI (**β = 0** .257, **p < 0.05** 249

). Following Vance et al. (2013), we established a final control variable model with optimal fit statistics by removing all the nonsignificant control variables. 6. Discussions and Conclusions A key objective of AI-powered RAs is

to form intimate and long-term **bonds with their users** and accompany **them** throughout **their** 96 everyday lives. Using an affordance lens, our study examines the effects of disclosure and explanation UI artifacts on users' perceptions of and PDC with these intelligent RAs. We explore the UI-design-artifact antecedents of REA and BEA and argue that when they are actualized, they affect users' perceptions (e.g., PE, PT, PI, and PD) and trust/distrust, which in turn influence their overall PDC. Drawing on the affordance theory and several other pertinent theoretical perspectives, we propose and empirically test an integrated research model using a novel FSM in a real e-commerce context (i.e., Amazon's recommendation engine). We employ both SEM and linear mixed methods to test the research model, which provides consistent results that strongly support our theorization. The multimethod approach allows us to check our results for robustness.

In the following sections, we discuss the study's key **findings, theoretical** and **practical implications, and limitations**	38

as well as avenues **for future research** . 6.1. **Summary of Results**	75

Our study has several interesting findings that provide insights into the inner workings of the black box of AI-powered RAs and has addressed our research questions. Regarding RQ1, we find strong empirical evidence of the linkage between IT artifacts and RA affordances. UI artifacts that manipulate RAT disclosure positively influence the perceived REA, whereas those that manipulate sponsored-recommendation disclosure positively influence the perceived BEA (H1a– b). The results of the subsequent SEM submodel analysis also indicate that RAT disclosure significantly increases the influence of REA on perceived effectiveness, perceived transparency, and perceived integrity, 142 whereas bias disclosure significantly increases the influence of REA on these user perceptions. Regarding RQ2, the main structural model was largely supported. As hypothesized, we find that an actualized REA increases perceived effectiveness, perceived transparency, and perceived integrity, whereas an actualized BEA increases perceived transparency and integrity but decreases perceived deceptiveness (H2, H3, H4a–b, H5a–b). Moreover, we find that, as predicted, perceived effectiveness and perceived integrity positively influence trust whereas perceived deceptiveness negatively influences trust (H6a, c, d). In addition, perceived integrity mitigates distrust, whereas perceived deceptiveness increases distrust (H6c, d). However, the effect of perceived transparency on trust (H6b) and the effects of perceived effectiveness and perceived transparency on distrust (H7a–b) are unsupported. The results of multiple serial mediation tests show that UI-disclosure artifacts have significantly positive indirect effects on PDC through serial mediators, including explaining affordances, user perceptions, trust, and distrust. Regarding RQ3, our MANOVA analysis indicates that users perceive the effectiveness of the three RATs differently. The results show that users perceive CF as the least effective of the three RATs. In addition, through serial moderation mediation analyses, we find that (1) prior knowledge

negatively moderates the positive effect of perceived effectiveness on trust in **the** 273

serial mediation path REA→PE→TR→PDC and (2) prior knowledge negatively moderates the positive effect of trust on PDC in the serial mediation path BEA→PD→TR→PDC. Interestingly, we also find that although the information about the RAT bias and about the sponsored-recommendation bias was similar, respondents perceived the graphical vignettes' succinct disclosure much more positively than they did the detailed disclosure of the inner workings of the black box provided by the article in the prior-knowledge manipulation. We contend that this interesting conundrum is likely caused by the fact that excessive disclosure of the AI black box could lead to counterproductive outcomes, such as information overload (Payne et al., 1988; Payne et al., 1993) and erosion of trust (Hosanagar & Jair, 2018; Waldman, 2020). Future research could further examine the effects of excessive disclosure of the RA black box. 143 6.

2. Theoretical and Practical Contributions **This study makes** significant **theoretical and practical** contributions. **First** 38

,

to the best of our knowledge, it **is** among **the first** empirical studies **to** apply affordance **theory to the** 130

RA discourse in IS research. Affordance theory has received substantial attention in other IS contexts, such as

social media (e.g., Karahanna et al., 2018), cyberbullying (**e.g**., Chan **et al** 57

., 2019), virtual reality and augmented reality (

e.g., Steffen **et al**., 2019), **and** gamification (**e.g**., Suh **et al** 57

., 2017). We empirically confirm that it also provides a powerful theoretical lens with which to analyze the digital companionship between AI-powered RAs and their users, which is the focus of the RA paradigm shift from facilitating short-term e-commerce transactions by matching products with customer preferences (Jannach et al., 2011) to forging long-term relationships with customers (Lee et al., 2017; Rzepka & Berger, 2018). Our study breaks new ground in understanding the relationships among IT artifacts, RA affordances, user perceptions, trust/distrust, and digital companionship. By empirically demonstrating that the salient explaining affordances provided by UI-design artifacts give rise to PDC, this study enriches the IS literature on human–computer relationships and long-term IS use continuance. Moreover, the study provides insights into the differential effects of the three major RATs (

i.e., content-based filtering vs. **collaborative filtering** vs. **hybrid** filtering) **and** 319

of users' prior knowledge of the recommendation methods and biased AI-driven RAs (i.e., high-level knowledge vs. low-level knowledge).

The findings of this study contribute to emerging research on **the** intersection **of** 145

IT design artifacts, users' perceptions of explainable AI-driven systems, and the effects on the perceived outcomes. Second, drawing on the TSRC (Reeves & Nass, 1996) and

the two-process view **of trust and distrust** building (**Komiak & Benbasat, 2008** 259

; Lewicki et al., 1998a),

we propose and empirically test an integrated theoretical **model** that investigates **the** effects **of** 53

how and why explanations and of sponsored recommendations on PDC through a series of mediators. Our findings strongly indicate that RAT-disclosure and bias-disclosure UI artifacts significantly increase customers' PDC through multiple mediation paths. The results highlight the key role of UI-design artifacts and the explaining affordances they provide in 144 shaping digital companionship between AI-powered RAs and end users. Therefore, we suggest that Amazon and other e-commerce platforms should consider implementing UI artifacts designed to provide salient explaining affordances that foster digital companionship with their users, which could eventually lead to higher profits. If the

results hold in other settings, our theoretical model could provide **a systematic explanation and prediction** 134 of the effects of UI-design artifacts on PDC from an affordance-based perspective. Third, our study is

the first to apply **the FSM** to RA research **using** UI- **design artifacts following the novel approach developed** by **Vance et al** 4

. (2015). Various RA studies have relied on data collected from students using experimental RAs. The FSM is particularly effective, because it enables us to simulate various graphical disclosure and explanation UI artifacts in a commercial AI-powered RA context and collect data from real Amazon customers. It

is neither an experiment nor a traditional survey but draws on the best of **both to provide a** 47

more sophisticated form of the scenario -based **method, because** it experimentally varies **the** textual elements **of** the scenario of **theoretical interest** 134

(Vance et al., 2013). The orthogonality achieved by the full factorial

allows us to clearly **distinguish between the different effects of** 47

the manipulations of the disclosure and explanation UI artifacts. Finally, the study's results have important implications for industry practitioners. Providers of AI- powered RAs can capitalize on the RAT- and bias-disclosure UI artifacts our study identifies. These artifacts can help companies reap substantial financial rewards by fostering and enhancing customers' PDC, which is a key driver of the long-term use of intelligent RA systems. Our findings suggest that the explaining affordances provided by UI artifacts can increase users' perceived effectiveness, perceived transparency, and

perceived integrity of the **RA** while **reducing** their **perceived** deceptiveness **of the RA** 48

. These user perceptions, in turn, increase users' trust in the RA while reducing their distrust, which eventually strengthens users' PDC with the RA. 6.3.

Limitations and Future Research This study has several limitations that point to avenues for future 47

research. First, although

the FSM yields 145 several benefits for our research design by allowing us to use sophisticated UI-artifact manipulations, a drawback to this method is that these disclosure and explanation UI artifacts are hypothetical and the MTurk data are not based on actual user experiences. Future research could explore opportunities for research partnerships with AI-powered RA providers and test these UI artifacts using a real RA system. Second, our study employs an online factorial survey to collect cross-sectional data over a brief period. Even though the theories our research model incorporates enable us to draw

causal inferences, the constraints of cross-sectional data may have **undermined our ability to establish** strong **causal relationships** 109

. Because user perceptions change with time and the experience of users, future longitudinal or experimental studies using a real RA system could complement and extend our findings. Third, we identify two key explaining subaffordances provided by UI-disclosure artifacts and find empirical support for them. Other explaining subaffordances and IT artifacts (not limited to UI) could also help unveil the black box of AI-powered RAs and strengthen users' PDC. Our study illustrates several ways to implement UI-disclosure artifacts, and future studies could test these artifacts in different contexts. In addition, future research could use a sequential mixed-methods design for the developmental purpose to examine key artifacts and their associated explaining affordances through a qualitative study, which through the triangulation of findings could provide stronger inferences than a single method and could lead to theoretically plausible answers to

the research questions (Venkatesh et al., 2013; Venkatesh et al., 2016 153

). Finally, our hypothetical vignettes provide different UI-disclosure designs. However, the extent to which individuals understand the purpose and content of these designs can vary from person to person. Thus,

an individual's comprehension level **is** highly **likely to influence** the effects **of** explaining affordances **on** 292

perceptions. Future research could use a small quiz following the presentation of a vignette to rate the level of a respondent's comprehension of the disclosure content (e.g., high vs. medium vs. low). A moderated mediation model could be used to further explore the moderating role of the level of a user's comprehension of the disclosure and explanation artifacts. 146 6.4. Conclusions Prior studies have predominantly adopted a utilitarian perspective to study the effects of explanation facilities and disclosure features on users' perceived transparency and trusting beliefs during the explicit user-preference-elicitation process. However, little is known about users' perceptions of disclosing and explaining specific RATs and AI biases. As the new generation of RAs evolves into intelligent and autonomous assistants that foster long-term digital companionships with users, a relational perspective on transparent and explainable RAs has become a necessity for both research and practice. Because these long- term relationships are process oriented, a mixed-methods approach including a qualitative component could be productive for future research. Using an affordance-based lens,

we develop a theoretical **model that** systematically **explains the** effects **of** unsealing **the** 335

black box of AI-powered RAs and highlights the salient role of explaining affordances and their associated UI-design artifacts in shaping users' PDC. We use a novel FSM

to empirically test the model, and the results strongly support most **of** 174

our hypotheses and shed light on interesting controversies. Our study offers a new theoretical perspective on AI-powered RAs; it is the first empirical attempt to use affordance theory to link UI-design artifacts and RAs' explaining affordances and to examine their impact on users' PDC. This study also provides industry practitioners with practical guidelines for designing more transparent and explainable AI-powered RAs using UI-design artifacts. 147 Essay 2 Appendices Appendix A. Survey Instrument Table A1. Prevignette Measures Variable Measure Age What is your age? 1 = 18–24 2 = 25–34 3 = 35–44 4 = 45–54 5 = 55–64 6 = 65–74 7 = 75–84 8 = 85 or older

Gender What is your gender? 1 = Male 2 = Female Race What is your race ? 1 = **White** /Caucasian 2 = **African American** 3 = **Hispanic** 4 = **Asian** 115

5 = Other Education (Edu)

What is the highest level of school **you have completed? 1 = Less than high school degree 2 = High school** graduate **3 = Some college** 156

(e.g., college student)

4 = Associate degree in college (2-year) 5 = Bachelor's degree in college (4-year) 6 = Master's degree 7 = Doctoral degree	68

Employment (Emp)

What is your current employment status ? 1 = **Employed full time** 2 = **Employed part time** 3 = **Unemployed looking for work** 4 = **Unemployed not looking for work** 5 = **Retired** 6 = **Student** 7 = **Disabled** Income **What is your** annual **income** range? 1 = **Less than** $20, **000**	79

2 = $20,000 to $39, **999 3** = $40, **000 to** $59, **999 4** = $60, **000 to** $79, **999 5** = $80, **000 to** $99, **999 6** = $100, **000**	104

or more Years with Amazon (CustExp) How long have you been an Amazon customer?

1 = 1-5 years 2 = 6-10 years 3 = 11-20 years 4 = 21 -27 **years**	198

Purchase frequency (PurFreq) How often do you purchase products from Amazon.com?

1 = 1-3 times a month 2 = Once a week 3 = 2 -4 **times a week 4 = More** than 4 **times a week**	76

Recommendation page usage (RecUse) How often do you use this personalized recommendation page? 1 =

Less than once a month 2 = 1-3 times a month 3 = Once a week 4 = 2 -4 **times a week 5 = More** than 4 **times a week**	76

Purchase based on recommendation (RecBuy) How often do you buy products recommended to you by Amazon? 1 =

Less than once a month 2 = 1-3 times a month 3 = Once a week 4 = 2 -4 **times a week 5 = More**	76

than 4 **times a week**

IT skills (ITSkills) How would you evaluate your skills of using information technology in general? [1 = low 7 = high] Trust propensity (TrustPro) How would evaluate your tendency to trust recommendations from a computer-mediated program? [1 = Low to 7 = High] Attitude toward AI (AttAI) To what extent do you think AI-powered systems will be a blessing to users? [1 = Definitely not a blessing to 7 = Definitely a blessing] Attitude toward RA aias (AttBias)

To what extent would **you agree with the following statement** 64

? Most AI-powered recommendation agents are biased. [1 = Strongly disagree to 7 = Strongly Agree] RA Experience (RAExp) How long have you been using a recommendation agent (e.g., Amazon product recommendation engine, Netflix movie recommendation engine, Google News App, etc.)? Slider [0-30] 158 Table A2. Post-vignette Measures Construct Items RAT explaining affordance (REA) Note: Please keep your Amazon recommendation page open as a reference when you answer the following questions. The Amazon AI-driven recommendation agent (RA) is hereafter referred to as “the system”. Wordings for affordance measurement were inspired by Chan et al. (2019, p. 4). Assuming the disclosure design in the snapshot were used by the Amazon recommendation page for you,

please indicate the degree to which you agree or disagree with the following statements: The 88

system would offer me the possibility to gain insight into… (REA1) why certain products are recommended to me. (REA2) what recommendation method is used. (REA3) how the recommendation method works. (REA4) the AI algorithm used to make recommendations to me. (new) Bias explaining affordance (BEA) (Chan et al., 2019, p. 4). The system would offer me the possibility to … (BEA1) obtain awareness of its bias which favors paid product sponsors. (BEA2) understand why

sponsored products appear **at the top of the recommendation** list. (BEA3) realize **the** 48

fact that other non-sponsored products may better fit my preferences and needs. (BEA4) understand its bias associated with sponsored recommendations. (new) Perceived effectiveness (PE) (Knijnenburg et al., 2012, pp. 498-499) (PE1) The system would make valuable recommendations based on a deep understanding of my personal interests. (PE2) The system would make valuable recommendations by sharing other similar users’ interests with me. (PE3) The system would give me valuable recommendations. Perceived transparency (PT) (Wang & Wang, 2019, p. 519); (Nilashi et al., 2016, p. 75) (PT1) It would be

easy for me to understand the inner workings of the **system** 48

. (PT2) I would understand the mechanisms of how the system makes its (PT3) The disclosure and explanation facilities would help me make better decisions. Perceived integrity (PI) (Wang & Benbasat, 2005, p. 100) (PI1) The system would provide unbiased recommendations. (PI2) I would consider this system to possess integrity. (PI3)

I would characterize this system's dealing with me as honest . (PI4) **This system** would appear **to be unbiased. Perceived** 48

deceptiveness (PD) (Han et al., 2018, p. 108) (PD1) The system would distort recommendations to favor sponsored products to deceive customers. (PD2) The system's AI-driven inner workings would be manipulated when making recommendations to me. (PD3) The system's AI-driven recommendation process would be manipulated to deceive customers. Trust (TR) (Wang et al., 2018a, p. 5213) (Komiak & Benbasat, 2006, p. 950) (TR1)

I believe the system's **dealings with me** would be **in my best interest** . (TR2) **I believe the** 22

system's recommendations would be trustworthy. (TR3)

I would feel comfortable about relying on the system **for my** purchase. (TR4 R) **I would feel** uncomfortable **about relying on** 196

the system. Distrust (DISTR) (Wang et al., 2018a, p. 5214) (DISTR1) The system would be capable of recommending products to me in a deceptive way. (DISTR2) The system would have

the ability to maliciously manipulate the products **recommended** . (DISTR3) The **system** would be **capable of deceiving users by recommending biased** 1

products. Perceived digital companionship (PDC) (Lee et al., 2017, p. 933) (PDC1) I would love to spend time with its AI-driven recommendation agent while shopping on Amazon. (PDC2) I would feel a sense of closeness to the Amazon AI-driven recommendation agent. (PDC3) I would feel that the Amazon AI-driven recommendation agent is committed to building a long-term customer relationship with me. (PDC4) I would feel attached to the Amazon AI-driven recommendation agent as a reliable intimate shopping assistant. Marker variable blue color (MBL) (Simmering et al., 2015) Blue Attitude Marker Variable (MBL1)

I prefer blue to other colors . (MBL2) **I like the color blue** . (MBL3) **I like blue clothes** 98

. Likert-type 7-point scale anchored in terms of frequency:

1 = Never, 2 = Rarely, 3 = Sometimes, 4 = About **half the time, 5 = Often, 6 = Most of the time, 7** = All **of** 105

the time Note: Items are measured on a

7-point Likert-type scale (1 = strongly disagree, 2 = disagree, 3 = slightly disagree, 4 = neutral, 5 = slightly agree, 6 = agree, 7 = strongly agree). Reverse-coded items 132

are indicated by an “R” next to the item codes. 160 Appendix B. Prior Knowledge Manipulation The following fictitious Bloomberg Businessweek article was inspired by (Wang & Wang, 2019)’s manipulation of prior knowledge. The Black Box Dilemma of Recommendation Agents By Liana Bass Recommendation agents (RAs) influence the choices we make each day - what product to buy, what book to read, which song to download, which movie/video to watch, and even which person to date. Nowadays, recommendation agents (RAs) powered by artificial intelligence have been widely used by major e-commerce applications (e.g., Amazon, Netflix, Spotify, Google News, Facebook, Twitter, Youtube, Tiktok, Instagram, etc.). However, many RAs do not reveal to customers why and how certain products are recommended. Customers do not obtain any insights into the inner workings of the "black box." These AI-driven RAs mainly use three methods enhanced by machine learning to make recommendations to you: 1) content-based filtering (CBF) techniques, which are based on your product preferences and recent purchases. This

method recommends items similar to the ones the user preferred in the past 216

through a

user modeling process, in which the interests and preferences **of users are inferred from the items** 168

that users interacted with	

previously. For example, YouTube recommends videos to viewers by analyzing their historical interests; Pandora recommends music that is similar to the music users have recently listened to; Google News recommends news items based on readers' interests, preferences, and previously viewed articles. 2) collaborative filtering (CF) techniques, which are based on what other similar customers have recently bought and liked. This method mimics

word-of-mouth recommendations and uses **the opinions** , tastes, and preferences **of like-minded people to generate recommendations**	207

. A typical example of collaborative filtering is Amazon's product recommendation agent which often displays "customers who bought this item also bought these other items." 3) hybrid filtering (HF) techniques, which utilize both content-based and collaborative filtering techniques. This method combines content-based filtering

and collaborative filtering techniques by **integrating individual and community preferences**	32

. A typical commercial example is Netflix, which makes recommendations of

movies that share similar **characteristics with** other **films that a** customer **has** previously watched and **rated highly (content-based filtering**	86

) as well as

by comparing the watching and searching patterns **of similar** customers (**collaborative filtering**	86

). In addition, many RAs do not provide neutral recommendations completely based on the best interests of the customers. Instead, businesses running these systems will need to balance the goals of maximizing profits and satisfying their customers' needs. For example, some of these RAs offer a "paid recommendation" program, which instills bias in the AI-driven system that puts sponsors' products or services at the top of the recommendation list, even though they might not best fit customers' preferences or needs. In recent years, an increasing number of mainstream AI-driven RAs have adopted the "paid recommendation" revenue model to increase business earnings. In addition, many e-commerce businesses allow third-party vendors to sell their products or services through their online platforms. To increase revenues, they build bias in the recommendation systems to favor their own products or services when generating recommendations for the customers. "Recommendation technologies, after all, are employed by companies to achieve their business goals. It is a legitimate and effective business practice for an e-commerce company to give preferences to paid recommendations and its own products or services," said Leon Carter, the CIO of RA.ai, a San Francisco- based technology firm specializing in AI-driven recommendation engines. For comments and questions, please email Liana.Bass@bloomberg.com 162 Appendix C. Vignette Manipulations Figure C1. Vignette 1 - Sponsored recommendation disclosure and explanation + No RAT disclosure or explanation Figure C2. Vignette 2 - Sponsored recommendation disclosure and explanation + Content-based filtering (CBF) disclosure or explanation Figure C3. Vignette 3 - Sponsored recommendation disclosure and explanation + Collaborative-filtering (CF) disclosure or explanation Figure C4. Vignette 4 - Sponsored recommendation (SR) disclosure and explanation + Hybrid filtering (HF) disclosure or explanation Figure C5. Vignette 5 - No sponsored recommendation (SR) or RAT disclosure and explanation Figure C6. Vignette 6 - No sponsored recommendation disclosure and explanation + Content-based filtering (CBF) disclosure or explanation Figure C7. Vignette 7 - No sponsored recommendation disclosure and explanation + Collaborative filtering (CF) disclosure or explanation Figure C8. Vignette 8 - No sponsored recommendation disclosure and explanation + Hybrid filtering (HF) disclosure or explanation Appendix D. Data Analysis Manipulation Checks Table D1. Effectiveness of RAT Disclosure Manipulation (Postvignette Constructs) Variable Mean Without RAT Disclosure SD Mean With RAT Disclosure SD Mean Diff

95% CI	for	**Mean Difference Effect Size (Cohen's d**	66

) t p RAT Explaining Affordance 2.457 1.459 5.620 0.975 -3.163 -3.377, -2.949 2.550 -29.031*** 0.000 Bias Explaining Affordance 3.170 1.773 4.366 1.922 -1.196 -1.562, -0.831 0.647 -6.426*** 0.000 Perceived Effectiveness 4.147 1.246 4.800 1.136 -0.653 -0.878, -0.428 0.548 -5.7*** 0.000 Perceived Transparency 2.818 1.482 4.959 1.280 -2.140 -2.398, -1.883 1.546 -16.338*** 0.000 Perceived Integrity 3.709 1.426 4.557 1.372 -0.848 -1.116, -0.58 0.606 -6.213*** 0.000 Perceived Deceptiveness 4.234 1.546 3.688 1.528 0.545 0.249, 0.842 0.355 3.611*** 0.000 Trust 3.800 1.402 4.452 1.330 -0.652 -0.912, -0.391 0.477 -4.91*** 0.000 Distrust 4.470 1.562 4.089 1.575 0.381 0.077, 0.685 0.243 2.458* 0.014 Perceived Digital Companionship 2.668 1.371 3.091 1.545 -0.423 -0.715, -0.132 0.290 -2.851** 0.005 Figure D1. Effectiveness of RAT Disclosure Manipulation (w/o vs. w) 6.00 5.00 4.00 Mean 3.00 2.00 1.00 0.00 REA BEA PE PT PI PD TR DISTR PDC w/o RAT Disclosure w RAT Disclosure BEA = bias explaining affordance; DISTR = distrust; PD = perceived deceptiveness; PDC = perceived digital companionship; PE = perceived effectiveness; PI = perceived integrity; PT = perceived transparency; REA = RAT (recommendation algorithm type) explaining affordance; TR = trust Table D2. Effectiveness of Bias Disclosure Manipulation (Postvignette Constructs) Variable Mean Without Bias Disclosure SD Mean With Bias Disclosure SD Mean Diff

95% CI	for	**Mean Difference Effect Size (Cohen's d**	66

) t p RAT explaining affordance 4.428 1.885 5.432 1.346 -1.003 -1.276, -0.731 0.613 -7.235*** 0.000 Bias explaining Affordance 2.785 1.552 5.639 1.032 -2.854 -3.074, -2.634 2.166 -25.515*** 0.000 Perceived effectiveness 4.434 1.206 4.903 1.129 -0.469 -0.661, -0.277 0.401 -4.792*** 0.000 Perceived transparency 3.927 1.635 5.100 1.315 -1.173 -1.419, -0.927 0.791 -9.381*** 0.000 Perceived integrity 3.965 1.448 4.830 1.256 -0.866 -1.089, -0.642 0.639 -7.602*** 0.000 Perceived deceptiveness 4.122 1.580 3.449 1.428 0.673 0.424, 0.921 0.447 5.325*** 0.000 Trust 4.014 1.380 4.642 1.287 -0.628 -0.847, -0.408 0.470 -5.616*** 0.000 Distrust 4.518 1.552 3.773 1.515 0.745 0.493, 0.997 0.486 5.813*** 0.000 Perceived digital companionship 2.825 1.484 3.193 1.532 -0.368 -0.615, -0.121 0.244 -2.929** 0.004 *p < .05, **p < .01, ***p < .001 Figure D2. Effectiveness of Bias Disclosure Manipulation (w/o vs. w) 6.00 5.00 4.00 Mean 3.00 2.00 1.00 0.00 REA BEA PE PT PI PD TR DISTR PDC w/o Bias Disclosure w Bias Disclosure BEA = bias explaining affordance; DISTR = distrust; PD = perceived deceptiveness; PDC = perceived digital companionship; PE = perceived effectiveness; PI = perceived integrity; PT = perceived transparency; REA = RAT (recommendation algorithm type) explaining affordance; TR = trust Table D3. Effectiveness of Prior Knowledge Manipulation Variable Know Mean Without Prior ledge SD Mean Knowledge SD With Prior Mean Diff

95% CI	for	**Mean Difference Effect Size (Cohen's d**	66

) t p RAT Explaining Affordance 5.051 1.653 4.715 1.801 0.336 0.054, 0.618 0.194 2.340* 0.020 Bias Explaining Affordance 4.193 1.921 3.979 1.985 0.215 -0.104, 0.534 0.110 1.322 0.187 Perceived Effectiveness 4.850 1.080 4.436 1.269 0.414 0.222, 0.606 0.351 4.231*** 0.000 Perceived Transparency 4.570 1.573 4.350 1.636 0.220 -0.042, 0.482 0.137 1.648 0.100 Perceived Integrity 4.599 1.298 4.110 1.517 0.489 0.259, 0.719 0.346 4.169*** 0.000 Perceived Deceptiveness 3.573 1.448 4.069 1.611 -0.495 -0.745, -0.245 0.323 -3.892*** 0.000 Trust 4.562 1.275 4.027 1.421 0.534 0.314, 0.755 0.396 4.761*** 0.000 Distrust 4.015 1.526 4.349 1.617 -0.334 -0.591, -0.077 0.212 -2.555* 0.011 Perceived Digital Companionship 3.248 1.582 2.725 1.396 0.523 0.279, 0.767 0.351 4.207*** 0.000 Figure D3. Effectiveness of Prior Knowledge Manipulation (w/o vs. w) 6.00 5.00 4.00 Mean 3.00 2.00 1.00 0.00 REA BEA PE PT w/o Prior Knowledge PI PD TR DISTR PDC w Prior Knowledge BEA = bias explaining affordance; DISTR = distrust; PD = perceived deceptiveness; PDC = perceived digital companionship; PE = perceived effectiveness; PI = perceived integrity; PT = perceived transparency; REA = RAT (recommendation algorithm type) explaining affordance; TR = trust Figure D4. The Effects of RAT Type Manipulation on Perceived Effectiveness

CBF = content-based filtering; CF = collaborative filtering; HF = hybrid filtering	97

; PE = perceived effectiveness; RAT = recommendation algorithm type Table D4. The Effects of RAT Type Manipulation on Perceived Effectiveness – Pairwise Comparison Dependent Variable: PE (I) RAT (J) RAT Mean Diff. (I-J) SE p CBF -0.727 0.138 0.000 Not disclosed CF -0.453 0.140 0.008 HF -0.761 0.136 0.000 Not disclosed 0.727 0.138 0.000 CBF CF 0.274

0.137 0.272 HF -0.034 0.133 1.000 Not disclosed 0.453 0.140 0.008 CF CBF -0.274 0.137 0.272 HF -0.308 0.135 0.136 Not disclosed 0.761 0.136 0.000 HF CBF 0.034 0.133 1.000 CF 0.308 0.135 0.136

CBF = content-based filtering; CF = collaborative filtering; HF = hybrid filtering 97

; PE = perceived effectiveness; RAT = recommendation algorithm type; SE = standard error Validity, Reliability, Multicollinearity and CMB Tests Table D5. Factor Loadings Items REA BEA PE PT PI PD TR DISTR PDC REA1 0.925 0.055 0.035 0.090 0.056 -0.007 0.004 -0.020 -0.016 REA2 0.908 -0.025 0.049 -0.026 0.015 -0.016 -0.007 0.033 -0.033 REA3 0.867 0.010 -0.052 -0.071 0.023 0.012 0.057 -0.002 0.021 REA4 0.757 -0.011 -0.009 -0.166 -0.074 0.009 -0.019 -0.058 0.082 BEA1 -0.038 0.937 -0.050 -0.053 0.059 0.012 0.011 0.016 -0.002 BEA2 0.032 0.948 0.011 0.042 -0.045 0.020 0.036 -0.023 0.021 BEA3 0.050 0.745 0.092 0.015 0.039 -0.108 -0.008 0.037 0.020 BEA4 -0.020 0.944 -0.008 -0.071 0.001 0.049 -0.006 -0.054 -0.006

PE1 -0 .042 - **0** .060 **0** .584 - **0** .117 **0** .053 **0** .080 **0** .143 - **0** .036 **0** 77 .162 **PE2 0** .007 **0** .042 **0** .741 - **0** .041 **0** .039 - **0** .065 **0** .022 - **0** .013 - **0** .009 **PE3 0** .071 **0** .046 **0** .814 **0** .021 **0** .023 - **0** .046 **0** .018 - **0** .032 - **0** .007 PT1 - **0** .007 **0** .043 **0** .030 - **0** .863 **0** .002 - **0** .003 **0.038 -0** .069 **0** .020 PT2 **0** .145 **0** .032 **0** .015 - **0** .678 **0** .105 - **0** .069 **0** .032 **0** .031 **0** .012 PT3 **0** .124 **0** .080 **0** .064 - **0** .655 **0** .054 - **0** .049 **0** .012 **0** .016 - **0** .026 PI1 - **0** .004 - **0** .006 **0** .154 - **0** .021 **0** .724 - **0** .039 - **0** .006 - **0** .093 - **0**

.008

PI2 -0 .016 **0** .034 **0** .033 - **0** .028 **0** .798 - **0** .008 **0** .026 - **0** .044 **0** 101 .037 **PI3 0** .030 **0** .028 - **0** .019 - **0** .024 **0** .876 - **0** .032 **0** .025 **0** .000 **0** .019 PI4 **0** .029 **0** .010 - **0** .037 - **0** .012 **0** .925 - **0** .021 **0** .036 **0** .013 **0** .019 PD1 **0** .002 - **0** .044 - **0** .013 **0** .011 - **0** .010 **0** .806 - **0** .016 **0** .072 - **0**

.031 PD2 0.059 0.040 0.004 0.075 -0.013 0.883 -0.004 0.038 -0.031 PD3 -0.058 -0.005 -0.019 -0.046 -0.031 0.878 -0.067 -0.013 0.005 TR1 -0.008 -0.011 -0.063 -0.004 0.030 0.002 0.799 -0.095 0.104 TR2 0.038 0.024 0.002 0.026 0.133 -0.080 0.777 -0.017 -0.045 TR3 -0.009 0.042 0.063 -0.029 0.048 -0.025 0.781 0.002 -0.023 TR4 0.027 0.020 0.090 -0.040 -0.067 -0.045 0.808 0.016 0.024 DISTR1 -0.026 -0.023 -0.050 -0.024 0.022 0.006 -0.015 0.947 0.018 DISTR2 0.000 0.021 0.020 0.046 -0.036 0.010 -0.052 0.856 0.034 DISTR3 0.005 -0.029 0.009 -0.010 -0.042 0.074 0.041 0.819 -0.083 PDC1 0.024 -0.071 0.086 0.006 0.147 0.043 0.118 -0.050 0.614 PDC2 -0.005 0.005 0.024 -0.019 0.002 -0.022 -0.023 -0.016 0.944 PDC3 0.023

0.050 -0.029 0.025 -0.033 -0.014 0.061 -0.053 0.876 PDC4 -0.002 0.020 0.004 -0.011 0.014 -0.048 -0.037 0.051 0.974 Extraction Method: Maximum Likelihood.

Rotation Method: Oblimin with Kaiser Normalization; Kaiser-Meyer-Olkin measure of sampling adequacy (KMO = **0**	205

.959) BEA = bias explaining affordance; DISTR = distrust; PD = perceived deceptiveness; PDC = perceived digital companionship; PE = perceived effectiveness; PI = perceived integrity; PT = perceived transparency; REA = RAT (recommendation algorithm type) explaining affordance; TR = trust Table D6. Means, Standard Deviations, CR, AVE and Construct Correlations

Mean SD CR AVE 1 2 3 4 5 6 7 8 9 1 . REA 4.887 **1**	199

.733 .950 .864 .929 2. BEA 4.089 1.954 .960 .857 .474 .926 3. PE 4.648 1.193 .893 .736 .491 .400 .858 4. PT 4.463 1.606 .939 .838 .831 .612 .637 .915 5. PI 4.360 1.429 .968 .884 .492 .507 .751 .659 .940 6. PD 3.815 1.548 .953 .871 -.322 -.363 -.588 -.492 -.798 .933 7. TR 4.301 1.373 .948 .819 .408 .422 .813 .598 .876 -.781 .905 8. DISTR 4.178 1.579 .951 .867 -.270 -.386 -.530 -.468 -.688 .814 -.719 .931 9. PDC 2.993 1.516 .954 .840 .228 .252 .537 .400 .568 -.514 .652 -.549 .916 CR (composite reliability) in the 3rd column,

AVE (average variance extracted) in **the** 4th column, and **square root of AVE** in bold **on the diagonal**	137

; BEA = bias explaining affordance; DISTR = distrust; PD = perceived deceptiveness; PDC = perceived digital companionship; PE = perceived effectiveness; PI = perceived integrity; PT = perceived transparency; REA = RAT (recommendation algorithm type) explaining affordance; TR = trust Table D7. Multicollinearity Analysis Variable

Unstandardized Coefficients β SE Standardized Coefficients β t p Tolerance **Collinearity Statistics VIF** Intercept **0**	135

.655 0.437 1.499 0.134 REA -0.039 0.045 -0.045 -0.880 0.379 0.357 2.801 BEA -0.047 0.030 -0.060 -1.528 0.127 0.606 1.649 PE 0.140 0.064 0.110 2.191 0.029 0.371 2.698 PT 0.044 0.058 0.046 0.750 0.454 0.248 4.037 PI 0.069 0.071 0.065 0.972 0.331 0.209 4.793 PD 0.082 0.057 0.084 1.430 0.153 0.275 3.641 TR 0.500 0.073 0.453 6.840 0.000 0.214 4.678 DISTR -0.212 0.049 -0.221 -4.316 0.000 0.358 2.790 Dependent Variable: PDC = perceived digital companionship BEA = bias explaining affordance; DISTR = distrust; PD = perceived deceptiveness; PE = perceived effectiveness; PI = perceived integrity; PT = perceived transparency; REA = RAT (recommendation algorithm type) explaining affordance; SE = standard error; TR = trust; VIF = variance inflation factor Table D8. Marker Variable Effect on Dependent Variable

Unstandardized Coefficients Standardized Coefficients Variable β SE β t p	Intercept	**3**		248

.019 0.240 12.569 0.000 Blue attitude marker -0.006 0.052 -0.005 -0.112 0.911 Dependent Variable: PDC = perceived digital companionship; SE = standard error Table D9. Correlations of Marker Variable with Other Constructs Variable REA BEA PE PT PI PD TR DISTR PDC BEA .464** PE .446** .387** PT .795** .594** .583** PI .464** .512** .710** .626** PD -.305** -.375** -.542** -.464** -.767** TR .383** .425** .760** .561** .835** -.735** DISTR -.265** -.383** -.491** -.441** -.670** .780** -.682** PDC .250** .268** .547** .392** .583** -.516** .663** -.548** MBL .040

n/s	-.002	**n/s**	.044	**n/s**	.013	**n/s**	-.002	**n/s**	.081	**n/s**	-.022	**n/s**	.070	**n/s**	-.005	**n/s**		172

MBL= Marker blue color, average r = 0.031, average p =0.551 PDC = perceived digital companionship; BEA = bias explaining affordance; DISTR = distrust; PD = perceived deceptiveness; PE = perceived effectiveness; PI = perceived integrity; PT = perceived transparency; REA = RAT (recommendation algorithm type) explaining affordance; TR = trust SEM Submodels Testing Table D10. Effects of RAT Disclosure (SEM Submodel Comparison) Without RAT Disclosure With RAT Disclosure Hypothesis

β SE CR p β SE CR p	H2. REA → PE	**0**	.475	**0**	.081 5.136	**0**	.000	**0**	.597	**0**	.069	10.785	**0**			93

.000 H4a. REA → PT 0.702 0.087 7.490 0.000 0.719 0.066 14.228 0.000 H4b. REA → PI 0.347 0.101 3.270 0.001 0.492 0.071 9.678 0.000 Note: CR = critical ratio; PE = perceived effectiveness; PI = perceived integrity; PT = perceived transparency; REA = RAT (recommendation algorithm type) explaining affordance; SE = standard error Figure D5. SEM Submodel Comparison – RAT Disclosure (w/o vs. w) w/o RAT Disclosure w RAT Disclosure 0.939 0.744 0.65 0.688 0.415 0.329 H1A. REA → PE H1B. REA → PT H1C. REA → PI PE = perceived effectiveness; PI = perceived integrity; PT = perceived transparency; REA = RAT (recommendation algorithm type) explaining affordance Table D11. Effects of Bias Disclosure (SEM Submodel Comparison) Without Bias Disclosure With Bias Disclosure Hypothesis

β SE CR p β SE CR p	H3. BEA → PT	**0**	.281	**0**	.039 6.883	**0**	.000	**0**	.330	**0**	.057	93
6.556	**0**											

.000 H5a. BEA → PI 0.330 0.050 5.872 0.000 0.349 0.074 4.969 0.000 H5b. BEA → PD -0.294 0.058 -5.101 0.000 -0.399 0.082 -6.203 0.000 BEA = bias explaining affordance; CR = critical ratio; PD = perceived deceptiveness; PI = perceived integrity; PT = perceived transparency; SE = standard error Figure D6. SEM Submodel Comparison – Bias Disclosure (w/o vs. w) w/o Bias Disclosure w Bias Disclosure 0.27 0.374 0.293 0.369 H 2 A . B E A → P T H 2 B . B E A → P I H 2 C . B E A → P D -0.298 -0.509 BEA = bias explaining affordance; PD = perceived deceptiveness; PI = perceived integrity; PT = perceived transparency Table D12. Effects of Prior Knowledge (SEM Submodel Comparison) Without Prior Knowledge With Prior Knowledge Hypothesis

β SE CR p β SE CR p	H3. REA → PE	**0**	.493	**0**	.045 8.103	**0**	.000	**0**	.501	**0**	.044	93
8.106	**0**											

.000 H4a. REA → PT 0.793 0.045 16.720 0.000 0.777 0.042 15.422 0.000 H4b. REA → PI 0.362 0.047 6.015 0.000 0.346 0.050 5.641 0.000 H3. BEA → PT 0.296 0.030 7.198 0.000 0.351 0.032 7.857 0.000 H5a. BEA → PI 0.354 0.036 5.950 0.000 0.425 0.043 6.985 0.000 H5b. BEA → PD -0.332 0.041 -5.709 0.000 -0.422 0.046 -7.361 0.000 BEA = bias explaining affordance; PD = perceived deceptiveness; PE = perceived effectiveness; PI = perceived integrity; PT = perceived transparency; REA = RAT (recommendation algorithm type) explaining affordance Figure D7. SEM Submodel Comparison – Prior Knowledge (w/o vs. w) w/o Prior Knowledge w Prior Knowledge 0.754 0.646 0.3630.354 0.2850.281 0.2140.253 0.3 0.212 H1A. REA → H1B. REA → H1C. REA → H2A. BEA → H2B. BEA → H3C. BEA → PE PT PI PT PI PD -0.235 -0.338 Model Testing with Linear Mixed Model (LMM) The SPSS linear mixed model only reports non-standardized coefficients, which were used in this section. Table D13. H1a Test - Fixed Effects of RAT Disclosure on REA Parameter/Hypothesis β SE df t p Supported Intercept 5.628 0.055 370.888 102.428 0.000 H1a: RAT Disclosure (w/o) → REA -3.196 0.107 528.991 -29.951 0.000 Yes Fit statistics: AIC = 1759.517; BIC = 1768.229; SE = standard error; reference level: with RAT disclosure REA = RAT (recommendation algorithm type) explaining affordance (REA) Table D14. Pairwise Comparison of REA Means (I) RAT Disclosure (J) RAT Disclosure Mean Difference (I-J) SE df p Not disclosed Disclosed -3.196 0.107 528.991 0.000 Disclosed Not disclosed 3.196 0.107 528.991 0.000 Table D15. H1b Test - Fixed Effects of Bias Disclosure on BEA Parameter/Hypothesis β SE df t p Supported Intercept 5.646 0.084 497.107 66.874 0.000 H1b: Bias Disclosure (w/o) → BEA -2.867 0.110 554.920 -25.977 0.000 Yes Fit statistics: AIC = 1981.236; BIC = 1989.948; SE = standard error; reference level: with bias disclosure BEA = bias explaining affordance Table D16. Pairwise Comparison of BEA Means (I) Bias Disclosure (J) Bias Disclosure Mean Difference (I-J) SE df p Not disclosed Disclosed -2.867 .110 554.920 .000 Disclosed Not disclosed 2.867 .110 554.920 .000 Table D17. H2, H4a, H5a Tests - REA Effects on User Perceptions Hypothesis β SE df t p Supported H2: REA→PE 0.290 0.023 457.224 12.638 0.000 Yes H4a: REA→PT 0.734 0.023 542.194 31.775 0.000 Yes H5a: REA→PI 0.381 0.028 471.803 13.731 0.000 Yes H2 Fit statistics: AIC = 1679.096; BIC = 1687.808; H4a Fit statistics: AIC = 1620.495;

BIC = 1629.207; H5a Fit statistics: AIC = 179 1885.459; BIC = 1894.171; SE = standard error PE = perceived effectiveness; PI = perceived Integrity; PT = perceived transparency; REA = RAT (recommendation algorithm type) explaining affordance Table D18. H3, H4b, H5b Tests - BEA Effects on User Perceptions Hypothesis β SE df t p Supported H3: BEA→PD -0.322 0.026 456.754 -12.226 0.000 Yes H4b: BEA→PT 0.493 0.027 570.492 17.990 0.000 Yes H5b: BEA→PI 0.391 0.024 487.978 16.483 0.000 Yes H3 Fit statistics: AIC = 1945.807; BIC = 1954.520; H4b Fit statistics: AIC = 1832.817; BIC = 1841.529; H5b Fit statistics: AIC = 1983.517; BIC = 1992.229; SE = standard error BEA = bias explaining affordance (BEA); PD = perceived deceptiveness; PI = perceived integrity; PT = perceived transparency Table D19. H6a-d Tests - Effects of User Perceptions on Trust Parameter/Hypothesis β SE df t p Supported Intercept 1.635 0.234 560.175 6.997 0.000 - H6a: PE→TR 0.377 0.034 562.997 11.191 0.000 Yes H6b: PT→TR -0.003 0.022 572.960 -0.114 0.910 No H6c: PI→TR 0.396 0.037 571.976 10.606 0.000 Yes H6d: PD→TR -0.210 0.028 549.817 -7.567 0.000 Yes Fit statistics: AIC = 1164.885; BIC = 1173.587; SE = standard error PD=perceived deceptiveness; PE=perceived effectiveness; PI=perceived integrity; PT=perceived transparency; TR=trust Table D20. H7a-d Tests - Effects of User Perceptions on Distrust Parameter/Hypothesis β SE df t p Supported Intercept 2.970 0.325 545.783 9.130 0.000 H7a: PE→DISTR -0.056 0.047 540.473 -1.196 0.232 No H7b: PT→DISTR -0.027 0.030 509.585 -0.881 0.379 No H7c: PI→DISTR -0.154 0.051 511.897 -3.023 0.003 Yes H7d: PD→DISTR 0.592 0.039 553.819 15.142 0.000 Yes Fit statistics: AIC = 1552.704; BIC = 1561.406; SE = standard error DISTR=distrust; PD=perceived deceptiveness; PE=perceived effectiveness; PI=perceived integrity; PT=perceived transparency; Table D21. H8 and H9 Tests Parameter/Hypothesis β SE df t p Supported Intercept 1.434 0.299 528.542 4.797 0.000 H8: TR→PDC 0.524 0.039 486.760 13.489 0.000 Yes H9: DISTR→PDC -0.167 0.036 534.548 -4.586 0.000 Yes Fit statistics: AIC = 1584.179; BIC = 1592.887; SE = standard error DISTR=distrust; PDC=perceived digital companionship; TR=trust Table D22. Summary of Model Fit Statistics Test Model Fit Statistics H1a AIC = 1759.517; BIC = 1768.229 H1b AIC = 1981.236; BIC = 1989.948 H2 AIC = 1679.096; BIC = 1687.808 H3 AIC = 1945.807; BIC = 1954.520 H4a AIC = 1620.495; BIC = 1629.207 H4b AIC = 1832.817; BIC = 1841.529 H5a AIC = 1885.459; BIC = 1894.171 H5b AIC = 1983.517; BIC = 1992.229 H6a-d AIC = 1164.885; BIC = 1173.587 H7a-d AIC = 1552.704; BIC = 1561.406 H8-9 AIC = 1584.179; BIC = 1592.887 Serial Mediation Tests Part 1. RAT Disclosure →Perceive Digital Companionship Indirect Effects (Figure D8-D13) Figure D8. Indirect Effects of RAT Disclosure on Perceived Digital Companionship, through REA, PE and TR Reference level: w/o RAT Disclosure; ***

p < 0.001; ** p < 0 .010; * **p < 0.05** ; ns = **not significant Figure** 57

D9. Indirect Effects of RAT Disclosure on Perceived Digital Companionship, through REA, PT and TR Reference level: w/o RAT Disclosure; ***

p < 0.001; ** p < 0 .010; * **p < 0.05; ns = not significant** 89

PI and TR Reference level: w/o RAT Disclosure; ***

$p < 0.001$; ** $p < 0$ .010; * $p < 0.05$; ns = not significant Figure 57

D11. Indirect Effects of RAT Disclosure on Perceived Digital Companionship, through REA, PE and DISTR Reference level: w/o RAT Disclosure; ***

$p < 0.001$; ** $p < 0$ .010; * $p < 0.05$; ns = not significant 89

PT and DISTR Reference level: w/o RAT Disclosure; ***

$p < 0.001$; ** $p < 0$ .010; * $p < 0.05$; ns = not significant Figure 57

D13. Indirect Effects of RAT Disclosure on Perceived Digital Companionship, through REA, PI and DISTR Reference level: w/o RAT Disclosure; ***

$p < 0.001$; ** $p < 0$ .010; * $p < 0.05$; ns = not significant Part 2 57

. Bias Disclosure →Perceive Digital Companionship Indirect Effects (Figure D14-D19) Figure D14. Indirect Effects of Bias Disclosure on Perceived Digital Companionship, through BEA, PT and TR Reference level: w/o Bias Disclosure; ***

$p < 0.001$; ** $p < 0$ .010; * $p < 0.05$; ns = not significant Figure 57

D15. Indirect Effects of Bias Disclosure on Perceived Digital Companionship, through BEA, PI and TR Reference level: w/o Bias Disclosure; ***

$p < 0.001$; ** $p < 0$ .010; * $p < 0.05$; ns = not significant 89

PD and TR Reference level: w/o Bias Disclosure; ***

$p < 0.001$; ** $p < 0$ .010; * $p < 0.05$; ns = not significant Figure 57

D17. Indirect Effects of Bias Disclosure on Perceived Digital Companionship, through BEA, PT and DISTR Reference level: w/o Bias Disclosure; ***

p < 0.001; ** p < 0 .010; * **p < 0.05; ns = not significant**	89

PI and DISTR Reference level: w/o Bias Disclosure; ***

p < 0.001; ** p < 0 .010; * **p < 0.05** ; ns = **not significant Figure**	57

D19. Indirect Effects of Bias Disclosure on Perceived Digital Companionship, through BEA, PD and DISTR Reference level: w/o Bias Disclosure; ***

p < 0.001; ** p < 0 .010; * **p < 0.05** ; ns = **not significant** MANOVA Testing **of** RAT **Effects**	57

Table D23.

Tests of Between Subject **Effects** of RAT **Source** Construct **Type III Sum of Squares df Mean Square F p Partial Eta Squared** REA 14000.865 **1**	118

14000.865 14681.936 0.000 0.971 BEA 8452.272 1 8452.272 2278.707 0.000 0.838 PE 10184.296 1 10184.296 7975.259 0.000 0.948 PT 10894.793 1 10894.793 6624.771 0.000 0.938 Intercept PI 9184.765 1 9184.765 4881.076 0.000 0.917 PD 6036.608 1 6036.608 2579.918 0.000 0.854 TR 8766.773 1 8766.773 4972.630 0.000 0.919 DISTR 7411.835 1 7411.835 2978.217 0.000 0.871 PDC 4218.848 1 4218.848 1775.001 0.000 0.801 REA 0.258 2 0.129 0.135 0.873 0.001 BEA 0.877 2 0.438 0.118 0.889 0.001 PE 8.231 2 4.116 3.223 0.041 0.014 PT 0.106 2 0.053 0.032 0.968 0.000 RAT PI 4.293 2 2.146 1.141 0.321 0.005 PD 2.474 2 1.237 0.529 0.590 0.002 TR 5.810 2 2.905 1.648 0.194 0.007 DISTR 0.836 2 0.418 0.168 0.845 0.001 PDC 9.006 2 4.503 1.895 0.152 0.009 REA 420.543 441 0.954 BEA 1635.775 441 3.709 PE 563.151 441 1.277 PT 725.248 441 1.645 Error PI 829.834 441 1.882 PD 1031.871 441 2.340 TR 777.485 441 1.763 DISTR 1097.509 441 2.489 PDC 1048.175 441 2.377 BEA = bias explaining affordance; DISTR = distrust; PD = perceived deceptiveness; PE = perceived effectiveness; PI = perceived integrity; PT = perceived transparency; REA = RAT (recommendation algorithm type) explaining affordance; SE = standard error; TR = trust; Figure D24. Pairwise Comparisons of PE Means DV (I) RAT (J) RAT

Mean Difference (I-J) SE p Lower Bound Upper Bound CBF CF **0**	7

.274 0.133 0.121 -0.046 0.594 HF -0.034 0.130 1.000 -0.346 0.277 PE CF CBF -0.274 0.133 0.121 -0.594 0.046 HF -0.308 0.132 0.059 -0.624 0.008 HF CBF 0.034 0.130 1.000 -0.277 0.346 CF 0.308 0.132 0.059 -0.008 0.624 DV = dependent variable; SE = standard error

CBF = content-based filtering; CF = collaborative filtering; HF = hybrid filtering	97

; PE = perceived effectiveness; RAT = recommendation algorithm type Table D25. User Self-Reported RAT Effectiveness Respondents answered a follow-up question after they read the fictitious Businessweek article that explains the three RATs (see Appendix B). It indicates that users perceived CF to be the least effective. Relating to your own experience, please provide your opinion on the effectiveness of the three major types of recommendation techniques (0-NOT effective, 10-Very effective). RAT Mean SD CBF 7.61 1.586 CF 5.01 1.864 HF 6.57 1.983

CBF = content-based filtering; CF = collaborative filtering; HF = hybrid filtering	97

; PE = perceived effectiveness; RAT = recommendation algorithm type Prior Knowledge Moderation Tests Table D26. Moderation Effect of Prior Knowledge on Perceived Effectiveness Model Summary → Trust R R^2

MSE F df1 df2 p 0 .769 **0** .591 **0** .779 165.028 **5** 572 **0** .000 β **SE t p LLCI ULCI constant -0** .134 **0** .245 -0.549 **0** .583 - **0** .615 **0** .346 REA **0** .017 **0** .035 0.486 **0** .627 - **0** .051 **0** .085 PE **0** .951 **0**	64

.053 18.011 0.000 0.847 1.054 PriorK 0.550 0.317 1.735 0.083 -0.073 1.173 Int_1 0.047 0.048 0.985 0.325 -0.047 0.140 Int_2 -0.204 0.070 -2.908 0.004 -0.342 -0.066

Product terms key: Int_1 : REA **x** PriorK **Int_2** : PE **x**	65

PriorK

R2-chng F df1 df2 p X*W 0 .005 5 .134 1 438 0	233

.024 M1*W 0.003 3.950 1 438 0.048 Dependent variable: TR Moderated Mediation Path: REA→PE→TR→PDC df = degree of freedom; LLCI = lower level confidence interval; PE = perceived effectiveness; PriorK = prior knowledge; REA = RAT (recommendation algorithm type) explaining affordance; MSE = mean squared error;

SE = standard error; ULCI = upper level confidence interval Table	40

D27. Moderation Effect of Prio r Knowledge on Trust → Perceived Digital Companionship

Model Summary R R2 MSE F df1 df2 p 0 .675 0 .455 1	64

.267 68.062 7 570 0.000 β

SE t p LLCI ULCI constant -0 .504 0 .518 - 0 .972 0 .332 -1.521 0 .514 BEA - 0 .021 0 .037 - 0 .557 0 .578 - 0 .094 0 .052 PD - 0 .005 0 .063 - 0 .084 0 .934 - 0 .128 0 .118 TR 0 .846 0	64

.073 11.642 0.000 0.703 0.988 PriorK 1.747 0.744 2.348 0.019 0.286 3.209 Int_1 0.015 0.053 0.271 0.787 -0.090 0.119 Int_2 -0.131 0.090 -1.452 0.147 -0.307 0.046 Int_3 -0.334 0.105 -3.197 0.002 -0.540 -0.129

Product terms key: Int_1 : BEA **x** PriorK **Int_2** : PD **x** PriorK **Int_3** : TR **x**	231

PriorK

Test(s) of highest order unconditional interaction(s): R2-chng F df1 df2 p X*W 0 .000 0.073 1 570 0	64

.787 M1*W 0.002 2.109 1 570 0.147 M2*W 0.010 10.223 1 570 0.002 Dependent variable: PDC Moderated Mediation Path: BEA→PD→TR→PDC BEA = bias explaining affordance; df = degree of freedom; LLCI = lower level confidence interval; PDC =

perceived digital companionship; PE = perceived effectiveness; PriorK = prior knowledge;

MSE = mean squared **error; SE = standard error** ; ULCI = upper **level confidence interval**	313

Demographic Information and Control Variables Table D28. Demographic Information Control Variables Sample Size = 289

Frequency Percent Age 18 - 24 25 - 34 35 - 44 45 - 54 55 - 64 65	203

- 74 33 81 81 44 35 15 11.4% 28.0% 28.0% 15.2% 12.1% 5.2% Gender Male Female 131 158 45.3% 54.7% Race White/Caucasian African American Hispanic Asian Other 225 24 12 19 9 77.9% 8.3% 4.2% 6.6% 3.1% Education

Less than high school degree High school graduate **Some college Associate degree Bachelor's degree Master's degree** Doctoral **degree**	176

1 20 75 14 131 42 6 0.3% 6.9% 26.0% 4.8% 45.3% 14.5% 2.1% Employment

Employed full time Employed part time Unemployed looking for work Unemployed not looking for work Retired Student Disabled	182

177 37 20 16 15 17 7 61.2% 12.8% 6.9% 5.5% 5.2% 5.9% 2.4% Income Less than $20,000 $20,000 to $39,999 $40,000 to $59,999 $60,000 to $79,999 $80,000 to $99,999 $100,000 or more 53 69 66 37 31 33 18.3% 23.9% 22.8% 12.8% 10.7% 11.4% Amazon customer experience (CustExp) 1-5 6-10 11-20 21-27 39 135 102 13 13.5% 46.7% 35.3% 4.5% Purchase frequency (PurFreq)

1-3 times a month Once a week 2-4 **times a week More than 4 times a week**	60

39 135 102 13 13.5% 46.7% 35.3% 4.5% Amazon recommendation page usage (RecUse)

Less than once a month 1 -3 **times a month Once a week 2-4 times a week More than 4 times a week**	141

141 102 29 14 3 48.8% 35.3% 10.0% 4.8% 1.0% Amazon purchase based on recommendation (RecBuy)

Less than once a month 1-3 times a month Once a week	220

158 107 17 54.7% 37.0% 5.9% 2-4

times a week More than 4 times a week 6	60

1 2.1% 0.0% 100.0% Scale Mean SD IT Skills (ITSkills) 1=Low to 7=High 5.16 1.178 Trust Propensity (TrustPro) 1=Low to 7=High 4.03 1.237 Attitude Toward AI (AttAI) 1=Definitely not a blessing to 7=Definitely a blessing 4.10 1.460 Attitude Toward RA Bias (AttBias) 1=Strongly disagree to 7=Strongly Agree 3.8400 1.378 RA Experience (RAExp) Years 8.36 5.255 Table D29. Effects of Control Variables on Perceived Digital Companionship

Parameter Estimate SE df	F	**p Intercept 2**	.402	**0**	.767 271	**3**	.131	**0**		166

.002 Age 0.005 0.062 271 0.073 0.942 Customer experience -0.271 0.113 271 -2.404 0.017 Purchase frequency 0.175 0.116 271 1.514 0.131 Amazon recommendation page usage 0.111 0.119 271 0.938 0.349 Amazon purchase based on recommendation 0.069 0.156 271 0.441 0.659 Gender -0.002 0.157 271 -0.011 0.991 Race -0.007 0.061 271 -0.121 0.904 Education -0.037 0.066 271 -0.565 0.573 Employment -0.010 0.050 271 -0.200 0.842 Income -0.006 0.059 271 -0.110 0.913 IT skills -0.055 0.072 271 -0.764 0.446 Trust propensity 0.095 0.087 271 1.096 0.274 Attitude toward AI 0.257 0.070 271 3.671 0.000 RA experience -0.008 0.015 271 -0.504 0.615 Attitude bias -0.087 0.061 271 -1.440 0.151 Fit statistics: AIC = 1925.053; BIC = 1933.702 Table D30. The Control Variable Model

Parameter Estimate SE df t p Intercept 2	.507	**0**	166

.377 286 6.648 0.000 Customer experience -0.311 0.100 286 -3.118 0.002 Attitude toward AI 0.369 0.052 286 7.146 0.000 Fit statistics: AIC = 1908.314; BIC = 1917.023 Essay 3. Key Affordances Affecting User-Perceived Companionship with AI-Driven Content Recommendation Agents: A Dual Perspective of User Engagement and Disengagement Abstract In recent years, AI-driven content recommendation agents (ACRAs) have grown exponentially in terms of market size, sophistication, and application domain. ACRAs have evolved from being primarily ad-hoc, task-based, and transaction-focused tools to intelligent assistants that focus on fostering long-term relationships with users, such as digital companionship. Given that research on the mechanisms that forge digital companionship in the recommendation agent (RA) discourse is scant and available findings are inconsistent, the present study seeks to better understand the emerging phenomenon of ACRAs using an

affordance perspective. We develop a dual-pathway **research model** to explain **how** RA **affordances** 317

simultaneously influence cognitive absorption, as a form of deep engagement, and algorithm aversion, as a proposed multidimensional form of disengagement, which in turn affect users' perceived digital companionship (PDC) with ACRAs. We empirically test the research model using online

survey data collected from 554 TikTok users. **The results show that** , via **the** 325

dual-pathway mechanism, the RA affordances provided by AI-driven artifacts foster cognitive absorption while mitigating algorithm aversion, leading to higher PDC. Moreover, we find that both cognitive absorption and algorithm aversion significantly mediate the effects of ACRA affordances on PDC, with cognitive absorption playing a more salient role and exerting a stronger influence on PDC. Notably, we also find that algorithm aversion has a strong negative effect on PDC for low-use TikTok users, whereas its effect on PDC for high-use users is very weak and nonsignificant. This important differential effect indicates that users who interact with an ACRA for longer periods of time and employ its recommendation algorithm more often will experience diminished algorithm aversion. These findings have important implications for IS researchers and ACRA designers, especially those involved in developing more engaging systems to foster PDC among users. Keywords: AI-driven content recommendation agents (ACRAs), recommendation agents (RAs), AI, RA affordances, cognitive absorption, algorithm aversion, perceived digital companionship (PDC) 1. Introduction The volume of diverse digital content generated on the Internet is exponentially increasing every year. This trend is partly attributable to digital information delivery, which allows users and content providers to create new or updated content in real time, thereby accelerating content publication (Karimi et al., 2018). The web and mobile platforms provide users with ubiquitous access to diverse digital content. With such vast amount digital content available online, users may find it overwhelming or difficult to discover new and interesting things to watch, read, or listen to. In response to this need, AI-driven content recommendation agents (ACRAs) have become increasingly p to help users discover new content that is relevant to their interests. Mainstream providers such as TikTok, YouTube, Netflix, Toutiao, and Google News, have implemented sophisticated ACRAs to more deeply engage users in content consumption from various sources. Research & Markets10 has projected that the global digital content recommendation engine market will reach $36.2 billion by 2027, with a compounded growth rate of 36.3% over the period 2020-2027. A recent HubSpot study showed that video is the top digital content format online, with short-form video being the most engaging content type and having the highest ROI compared to any other content format (Hubspot, 2022).

Short-form video platforms , such as **TikTok, YouTube Shorts, Instagram Reels** 318

, and Snapchat Spotlight, are experiencing tremendous growth and are displacing traditional social media, such as Facebook. According to DataIntelo's latest market research report11, the global short-form video platform

market is projected **to grow from** $1.1 **billion in 2020 to** $2.3 **billion** 278

by 2030, with North America expected to lead throughout the forecast period with an estimated revenue share of over 40%. TikTok, for example, has undergone phenomenal growth in recent years, surpassing both Google and Facebook as the world's most popular domain in 2021 (Tomé & Cardita, 2021). The most conspicuous feature of TikTok is its algorithm-driven and content-oriented platform, the popularity of which largely depends on its powerful ACRA and content distribution strategies (Zhao, 2021). 10 https://www.researchandmarkets.com/reports/4804636/content-recommendation-engine-global-strategic 11 https://dataintelo.com/report/short-video-platforms-market/ Prior information systems (IS) research has predominantly investigated recommendation agents (RAs) for online products or services through the technology acceptance model (TAM) and the trusting beliefs lens. These RAs are designed to reduce the cognitive load involved in

gathering, screening, and evaluating the vast amounts **of product** and service **information available** 276

online; and they do so by explicitly eliciting customers' needs and preferences to identify—and subsequently market—products and/or services that appeal to individual users (

e.g., Komiak & Benbasat, 2006; Wang & Benbasat , 2016; Xiao & **Benbasat** , 2007). **In** 18

contrast to generic product-brokering RAs, ACRAs are designed to aggregate massive volumes of digital content from a variety of sources and as such must possess a deep understanding of the semantics of unstructured data (Beel et al., 2016; Ghasemaghaei et al., 2019; Pazzani & Billsus, 2007; Rajaraman et al., 2014) and be capable of providing more personalized and immersive experiences based on user preferences (Lops et al., 2011). One key success factor for ACRAs is their capacity to implicitly learn user preferences and behaviors through continuous human–AI interactions for the purpose of ensuring long-term continuance intention. Compared with the large volume of research on traditional RAs, few studies have focused on long-term relationship building through repeated and deep user engagement as exemplified by ACRAs. To capture the essence of this symbiotic human–AI relationship, we propose a novel construct, perceived digital companionship (PDC), which refers to a combination of attachment, commitment, and intimacy between users and AI-driven RAs. The PDC metaphor draws on theoretical perspectives on the characteristics and qualities of human relationships (Carolus et al., 2018). Interactions between ACRAs and users may culminate in long-term PDC, which, in turn, could promote long-term continuance intention. However, in the IS discipline, research on ACRAs is still nascent. Only a few extant studies have examined digital content RAs, predominantly focusing on constructs such as recommendation accuracy, user satisfaction, and transparency (

e.g ., Kohler **et al** ., 2011; Liang **et al** ., 2006). **Little is known** about **how** 44

ACRAs deeply engage users and build long-term PDC with them, nor have the mechanisms through which the artifacts affect users' relationships with these RAs been well examined in the IS discourse. Al-Natour and Benbasat (2009) pointed out there are two major types of IT artifacts: 1) those static ones that produce 194 salient utilitarian outcomes such as enhancing productivity, and 2) those dynamic ones that focus on social context and user-artifact interactions. In particular, the dynamics artifacts (e.g., user virtual personality, exploration and discovery, autonomous implicit adaptation, semantic profiling, contextual information sensors) focus on social context and RA-user interactions to produce relational outcomes, especially those that allow for user experience and deep engagement (e.g., aesthetic experience, flow experience). One promising approach to conceptualizing such deep engagement is provided by the theory of

cognitive absorption. Cognitive absorption was defined **by Agarwal and Karahanna (2000** 70

, p. 665)

as "a state of deep involvement with software" and **is theorized to be exhibited through** five **dimensions: temporal dissociation, focused immersion, heightened enjoyment** (or joy), **control, and curiosity** 20

. Cognitive absorption

has been widely **adopted in IS research as a construct** 3

reflecting deep engagement from both cognitive and hedonic perspectives, and

it serves as a key antecedent to salient beliefs about information technology (Agarwal & Karahanna, 2000 113

). Researchers have found that cognitive absorption positively influences users' continuance intention in the product-brokering RA context (Acharya et al., 2022; Ghasemaghaei, 2020). Our

study thus proposes the concept of cognitive absorption **to characterize** deep **engagement** 3

and to serve as a key construct to account for users' PDC in the context of ACRAs. Despite the widespread belief that RAs can benefit users through deep engagement, prior

studies have highlighted the difficulty of sustaining user engagement 3

due to factors such as aversion (Smith et al., 2022), reactance (Fitzsimons & Lehmann, 2004), distrust (Komiak & Benbasat, 2008), and dissatisfaction (Smith et al., 2022). Under certain circumstances, users may react negatively to AI recommendation algorithms and consequently disengage from RAs (Fitzsimons & Lehmann, 2004; Ma et al., 2021; Ochmann et al., 2020). This disengagement can ultimately lead to terminating the relationship between users and RAs. Therefore, we posit that users' disengagement from interactions with ACRAs is another key determinant of PDC. However, a rigorous and systematic

approach to developing a research construct that holistically **reflects** disengagement **is lacking in the IS literature** . To examine **the** 3

precise nature of disengagement in the ACRA context, we drew inspiration from emerging human–AI research on algorithm aversion, which 195 refers to the phenomenon of users biasedly displaying negative behaviors and attitudes toward algorithms and preferring human agents even when evidence-based algorithms are proven to be superior (Dietvorst et al., 2015; Jussupow et al., 2020). Currently,

the concept of algorithm aversion **has not been well established in the IS literature** 3

and lacks a unified or widely accepted definition (Jussupow et al., 2020). In particular,

it is unclear how algorithm aversion relates to research streams 10

on IT artifacts and affordances, resistance toward AI-powered systems, and the effects of algorithms on user relationships. Against this backdrop, we examined the characteristics of algorithm aversion from a multidimensional perspective and further investigated its influence on PDC as well as its antecedents through an affordance lens. Building on

the work of Dietvorst **et al** . (2015) **and** Jussupow **et al. (2020** 40

), we theoretically conceptualized algorithm aversion in the context of ACRAs by integrating theoretical perspectives of psychological reactance and distrust. We further extended algorithm aversion into a multidimensional construct exhibited through the four dimensions of human preference, psychological reactance, distrust, and dissatisfaction, which we posited to be a proximal antecedent of PDC. Prior RA research has not explored the potential interplay between engagement and disengagement concurrently in an integrated model. Our research filled this gap by proposing a dual-pathway model in which cognitive absorption (deep engagement) and algorithm aversion (disengagement) act as two explanatory mechanisms for users' perceived companionship with ACRAs. Further, we drew on affordance theory to explore the antecedents of cognitive absorption and algorithm aversion. The affordance perspective proposes that, to engage users, it is essential to create IT artifacts that provide specific technological and affective affordances (

Chan et al., 2019 ; Hayashi **et al., 2016** ; Van Vugt **et al** 124

., 2006). The affordance lens was ideal in our research context because it clarified the symbiotic relationship between technological capabilities and users' goals and actions by treating their entanglement as a unit of analysis (Grgecic et al., 2015; Majchrzak et al., 2013). Moreover, the affordance lens

allows researchers to assess how users perceive the actions they can perform while interacting with technological features 3

(Chan et al., 2019). 196 To identify the key RA artifacts that can facilitate deep user engagement while mitigating user disengagement, we turned to previous literature on RA characteristics and features (

e.g., Komiak & Benbasat, 2006 ; Qiu & Benbasat, 2009; **Wang et al** ., 2016; **Wang** & Wang, 243

2019; Xiao & **Benbasat, 2007**

), as well as studies of AI features implemented in RAs (e.g., Hariri et al., 2015b; Hopfgartner & Jose, 2010). Next, we drew on affordance theory to identify four key affordances (i.e., personalizing affordance, interacting affordance, knowledge-seeking affordance, and serendipitizing affordance) and matched them with the RA artifacts. Finally, we developed and empirically tested a dual-pathway nomological network that includes cognitive absorption and algorithm aversion as mediators between actualized RA affordances and PDC. Specifically, we sought to address the following research questions: RQ1: What are the key factors that influence users' perceived companionship with ACRAs? RQ2: How do RA affordances influence users' engagement and disengagement with ACRAs? Scientifically, this research contributes to the IS literature by extending algorithm aversion into a multidimensional construct and validating it as a power construct that explains user disengagement from ACRAs. This work also advances scientific knowledge of the dynamics between user engagement and disengagement by integrating cognitive absorption and algorithm aversion into a dual-pathway model. Moreover,

by demonstrating how the technological and affective **affordances of** ACRAs **can** facilitate 3
deep **engagement**

while mitigating disengagement through a nomological network, the research generated scientific explanations and empirical justifications for how and why ACRAs foster long-term PDC with users. Practically, this study contributes design guidelines on ACRAs by delineating their key affordances and mechanisms, which can in turn assist providers in building long-term PDC with users and eventually increasing revenues. 2. Theoretical Background

In this section, we first conceptually **define** ACRAs and highlight **the key** differences 311
between ACRAs **and**

traditional RAs. We then briefly review previous theoretical perspectives and suggest the use of an affordance lens with a focus on user deep engagement and disengagement to fill the current research gap. Next, we leverage the theoretical perspectives of cognitive absorption, algorithm aversion, and 197 psychological reactance to theorize a dual-pathway model incorporating these two concepts. Specifically, we propose cognitive absorption as a form of deep engagement and theoretically extend algorithm aversion as a multi-dimensional construct representing disengagement. By conceptualizing cognitive absorption as a form of deep engagement, we can better understand the ways in which ACRAs can facilitate user immersion and involvement. Similarly, by extending the concept of algorithm aversion to include multiple dimensions, we can more accurately capture the various ways in which users may disengage from ACRAs and the factors that influence this behavior. Finally, we introduce the affordance theory and identify four salient affordances that could affect users' PDC with ACRAs. 2.1. AI-driven Content Recommendation Agents (ACRAs) Defined RAs in the product-brokering context are defined as “software agents that elicit the interests or preferences of individual users for products, either explicitly or implicitly, and make recommendations accordingly” (Xiao & Benbasat, 2007, p. 137). Prior research has used a variety of terms to describe these personalized technologies, such as RAs, recommendation systems, and recommender systems (Beel

et al., 2016 ; Bobadilla **et al., 2018** ; Pazzani & Billsus, **2007** ; Rajaraman **et al** 69

., 2014; Xiao & Benbasat, 2007, 2014b). Most existing IS studies have focused on commercial product- or service-brokering

RAs (e.g ., Borràs **et al** ., 2014; Xiao & **Benbasat** , 2007; **Xu et al., 2014** 1

), which are mainly based on traditional keyword matching database technologies, rating systems, and collaborative filtering techniques (Kim & Kim, 2001). In this application domain, an RA is a personalized and advice-giving technology (Komiak & Benbasat, 2006) that helps customers overcome information overload (Aljukhadar et al., 2012; Maes, 1994), thus improving their decision making (Häubl & Trifts, 2000) and reducing uncertainty about buying products or services online (Hong & Pavlou, 2014). ACRAs emerged due to recent technological advancements in deep learning, big data (Moreno & Redondo, 2016; Zhang et al., 2018), and ubiquitous mobile computing (He et al., 2019). Nowadays, deep learning (DL), a subfield of machine learning that uses complex algorithms that mimic human neural network, is bustling with paradigm-shifting innovations in RAs (Zhang et al., 2018), especially in the 198 application domains of deep representations of

images, text, and interactions in a unified, joint framework (Zhang et al 227

., 2017). Integrating these concepts, we formally define an ACRA as A personalized technology powered by AI recommendation algorithms that semantically analyzes digital content (e.g., texts, images, videos, audios) from a variety of online sources and places a long-term focus on relationship building through repeated user engagement based on autonomous and implicit adaptation to users’ evolving behaviors and preferences. 2.2. Prior Theoretical Perspectives Previous studies have investigated the effects of RA design artifacts, including the effect of explanation facilities on trust (Wang et al., 2016), of warning messages on perceived bias in recommendations (Xiao & Benbasat, 2015), of humanoid embodiment and output modality on social presence (Qiu & Benbasat, 2009), and of explicit and implicit feedback on satisfaction (Liang et al., 2006). Xiao and Benbasat (2007) seminal review paper theorized the influences of RA use and RA characteristics on RA adoption intentions, which has subsequently guided numerous studies on traditional product-brokering RAs. Based on two major streams of empirical research on RAs, Xiao and Benbasat’s model adopts

a dual focus on (1) consumers' decision-making processes and outcomes with the assistance of RAs, and (2) users' subjective evaluation of RAs (Xiao & Benbasat, **2007** 49

). Xiao and Benbasat (2007) presented an adequate theoretical framework with 28 propositions

to account for phenomena relating to the outcomes of product-brokering **RA use in e- commerce** 32

and providing directions for future research. These earlier studies concentrated on theoretical frameworks of technology acceptance with a limited focus on the factors responsible for capturing user experience (Acharya et al., 2022). In contrast to traditional product-brokering RAs, which heavily rely on explicit elicitation methods to understand user preferences, ACRAs have a long-term focus on relationship building through repeated user engagement based on autonomous and implicit adaptations to the evolving preferences of users. The conceptual framework by Xiao and Benbasat (2007) lacks constructs and mechanisms necessary for addressing these new tensions. Similarly, few studies have examined the effects of salient RA affordances on symbiotic digital relationships from the standpoint of user engagement and disengagement. Earlier IS research considered user

engagement as a desirable, even essential, human response to computer-mediated activities (Laurel 221

, 2013). Engaging interactions are sought after by both application developers and users, underscoring the importance of understanding how to make IS more engaging (O'Brien & Toms, 2008). In particular, one view of deep engagement argues that IS should be designed to afford users the experience of sensing focused immersion, temporal dissociation,

heightened enjoyment, control, and curiosity (Agarwal & Karahanna, 2000 ; Lowry **et al** 271

., 2013a; Suh et al., 2017). This holistic system involvement may culminate in an endearing bond and long-term relationship with users. As a result, more businesses have adopted

advances in AI, natural language processing, and machine-learning capabilities to provide accurate , personalized **and in-the-moment** 185 recommendationsiv to deeply engage users (Acharya et al., 2022; Bhattacharya & Lamkhede, 2022). Conversely, emerging research suggests that humans may have ambivalent attitudes toward AI-driven algorithms (Kang & Lou, 2022). Whereas users often welcome the unprecedented efficiency and convenience AI offers, they may negatively react to AI recommendation algorithms and disengage from RAs under certain circumstances (Fitzsimons & Lehmann, 2004; Ma et al., 2021; Ochmann et al., 2020). This disengagement can ultimately lead to terminating the relationship between users and RAs. 2.3.

Cognitive Absorption Theory Cognitive absorption is defined as "the state of deep involvement with software" (**Agarwal & Karahanna, 2000, p** . 665) **and is** 5

rooted in three closely interrelated concepts: the

state of flow (Csikszentmihalyi, 1990), cognitive **engagement (Webster & Ho, 1997), and absorption (Tellegen & Atkinson, 1974** 37

)v. As an intrinsic motivation-related construct, cognitive absorption "is important to the study of technology use behavior because it serves as a key antecedent to salient beliefs about an information technology" (Agarwal & Karahanna, 2000, p. 666). Notably, cognitive absorption can be considered

a positive and **enjoyable experience when a user is** deeply engaged **in** interacting **with** 270

a new technology (Ghasemaghaei, 2020). According

to Agarwal and Karahanna (2000), cognitive absorption can be conceptualized **as a second-order construct** 25

exhibited through five dimensions: (1) temporal dissociation , which is **the inability to register the passage of time while engaged in interaction** ; 200 (2) **focused immersion** , which is **the experience of total engagement** in which **other attentional demands are, in essence, ignored; (3) heightened enjoyment** 46 (or joy for short), which refers to pleasurable aspects of the interaction and

represents a synthesis of the intrinsic interest dimension of flow (Webster & Martocchio, **1993) and** 46
perceived enjoyment (Davis et al., 1992

); (4) control, which is

the user's perception of being in charge of the interaction; (5) curiosity , which is **the extent** to 99
which an **experience arouses an individual's sensory and cognitive curiosity (Malone, 1981**). In
the

IS literature,

cognitive absorption theory **has been** widely applied **to** understand **the formation of user** 28

trust and intention to use new technologies. Numerous extant studies have generated empirical evidence that cognitive absorption can induce and strengthen technology adoption and continuation behaviors (e.g., Acharya et al., 2022; Balakrishnan & Dwivedi, 2021;

Chandra et al., 2012 ; Ghasemaghaei, 2020; **Goel et al., 2011; Lowry et al** 37

., 2013a). However,

to our knowledge, no previous **studies have empirically** investigated **the** influence **of** 180

cognitive absorption on users' PDC with an AI-driven technology. Therefore, our study conceptualized cognitive absorption as deep engagement in a dual-pathway model (Figure 1) and examined its effect on users' PDC with ACRAs. 2.4. Algorithm Aversion and Proposed Extensions Algorithm aversion research originated with a comparison of people's reactions to

mathematical or computational problem-solving approaches with their reactions **to holistic** and 10