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Explaining how algorithms work reduces consumers' concerns regarding the collection of personal data and promotes AI technology adoption

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Abstract

Consumers' concerns about how companies gather and use their personal data can impede the widespread adoption of artificial intelligence (AI) technologies. This study demonstrates that mechanistic explanations of AI algorithms can inhibit such data collection concerns. Four independent online experiments show a negative effect of detailed mechanistic explanations on data collection concerns (Studies 1a and 1b), as well as mediating influences of a subjective understanding of how AI algorithms work (Study 2) and increased the likelihood to adopt AI technologies after data collection concerns have been mitigated (Study 3). These findings contribute to research on consumer privacy concerns and the adoption of AI technologies, by identifying (1) a new inhibitor of data collection concerns, namely, mechanistic explanations of AI algorithms; (2) the psychological mechanisms underlying mechanist explanation effects; and (3) how diminished data collection concerns promote AI technology adoption. These insights can help companies design more effective communication strategies that reduce the perceived opacity of AI algorithms, reassure consumers, and encourage their adoption of AI technologies.

KEYWORDS

adoption of AI technologies, data collection concerns, mechanistic explanations of AI algorithms, privacy

1 | INTRODUCTION

Artificial intelligence (AI) technologies deliver value to customers by leveraging algorithms that are trained using the consumers' personal data (Du & Xie, 2021). Euphoric projections about the spread of AI technologies once offered predictions of 50 billion connected devices by 2020 (Evans, 2011); reality has not quite achieved such levels, such that only 10 billion connected devices currently are in use (Transforma Insights, 2020). The road to mass adoption of AI technologies thus appears longer and bumpier than expected. But why are consumers reluctant to adopt AI technologies?

The reasons seemingly reflect both technological (e.g., use complexity, value offered, risk) and consumer (e.g., data collection concerns, desire to avoid dependency; Mani & Chouk, 2018; Park et al., 2021) factors. Data collection concerns, defined as consumers' worries about how companies gather and use their personal data (Smith et al., 1996), combined with AI technologies' powerful abilities to collect and process huge amounts of personal data, are particularly influential in prompting consumers to avoid or delay their adoption (Insider Intelligence, 2020); a reported 87% of sales delays stem from consumers' privacy concerns (Cisco, 2019).

In a preliminary survey, we conducted as a foundation for the current study, we recruited 669 US respondents from Prolific (48.9% men; 41.3% 18–30 years, 17.9% 31–45 years, 30.2% 46–60 years, and 10.6% older than 60 years) and asked them about their perceptions of technological features of AI technologies, their individual characteristics, and their intentions to purchase or spread positive word of mouth (WOM) about AI technologies. In a two-step cluster analysis (see Appendix A), we identified three clusters: Innovators ($N = 222$), early majority ($N = 269$), and skeptics ($N = 178$). As Figure 1 indicates, data collection concerns are the primary determinant of cluster membership ($F(2, 666) = 329.84$; $p < 0.001$), such that the early majority and skeptics exhibit higher data collection concerns and lower purchase and WOM intentions. In contrast, innovators score lowest on data collection concerns and highest on purchase and WOM intentions. These findings confirm that data collection concerns can hinder both purchase and WOM intentions—particularly crucial issues, considering that most of the respondents express strong data collection concerns. The mainstream diffusion of AI technologies thus may require tactics to reduce these data collection concerns, which in turn demands a clear identification of inhibitors that can neutralize or mitigate their adverse effects.

In prior attempts, scholars and practitioners have proposed various business factors and marketing strategies (Martin & Murphy, 2017; Mattison Thompson & Siamagka, 2022), often related to the seemingly essential need to grant consumers control over their personal data management (e.g., Tucker, 2014; Xu et al., 2012). However, it may be equally relevant to provide consumers with explanations of AI algorithms that detail the uses of their data (Bhalla, 2020). Most consumers are not computing experts and perceive an AI algorithm as a “black box” (Rai, 2020). Its methods for gathering and using personal data to make decisions seem unclear, leaving them to worry about whether they can trust it with their personal information (Puntoni et al., 2021; Thomaz et al., 2020). Google already gives customers insights into why its algorithm has generated a particular outcome (Kelion, 2019), and the European Union requires companies to explain AI systems' decision-making process as part of its General Data Protection Regulation (Skiera et al., 2022). Explaining how the AI algorithm works can increase consumers' trust in AI-based recommendation agents (Wang & Benbasat, 2007), satisfaction with the algorithm's decisions (Tomaino et al., 2020), and the likelihood of using AI-based services (Cadario et al., 2021). However, prior studies do not explicitly identify a mechanistic explanation of AI algorithms as a potential inhibitor of data collection concerns, nor do they specify how much detail is required in an explanation for it to be effective. Such information is essential to practitioners, who need to decide whether and how much to explain their algorithms, in ways that encourage consumers to overcome their concerns and adopt AI technologies.

Therefore, in this study, we draw on prior studies of data collection concerns (Martin & Murphy, 2017; Martin et al., 2017; Mattison Thompson & Siamagka, 2022), mechanistic explanations (Craik, 1943; Glennan, 1996), and consumers' subjective understanding of product functioning (Cadario et al., 2021; Fernbach et al., 2013) to propose that providing consumers with detailed mechanistic explanations of AI algorithms can reduce their data collection concerns (Studies 1a and 1b). When exposed to such explanations, consumers gain an increased subjective understanding of how AI algorithms work and express diminished data collection concerns (Study 2). These lower data collection concerns then increase their tendency to adopt AI technologies (Study 3).

In turn, we make three main contributions to the literature on privacy (e.g., Scarpi et al., 2022), data collection concerns (e.g., Hsu & Lin, 2016; Malhotra et al., 2004; Smith et al., 1996), and AI technology adoption (e.g., Mariani et al., 2022). First, rather than privacy inhibitors ensconced in a firm's privacy policies or characteristics (e.g., control, organizational privacy ethical care, brand credibility; Jain et al., 2022; Martin & Murphy, 2017; Mattison

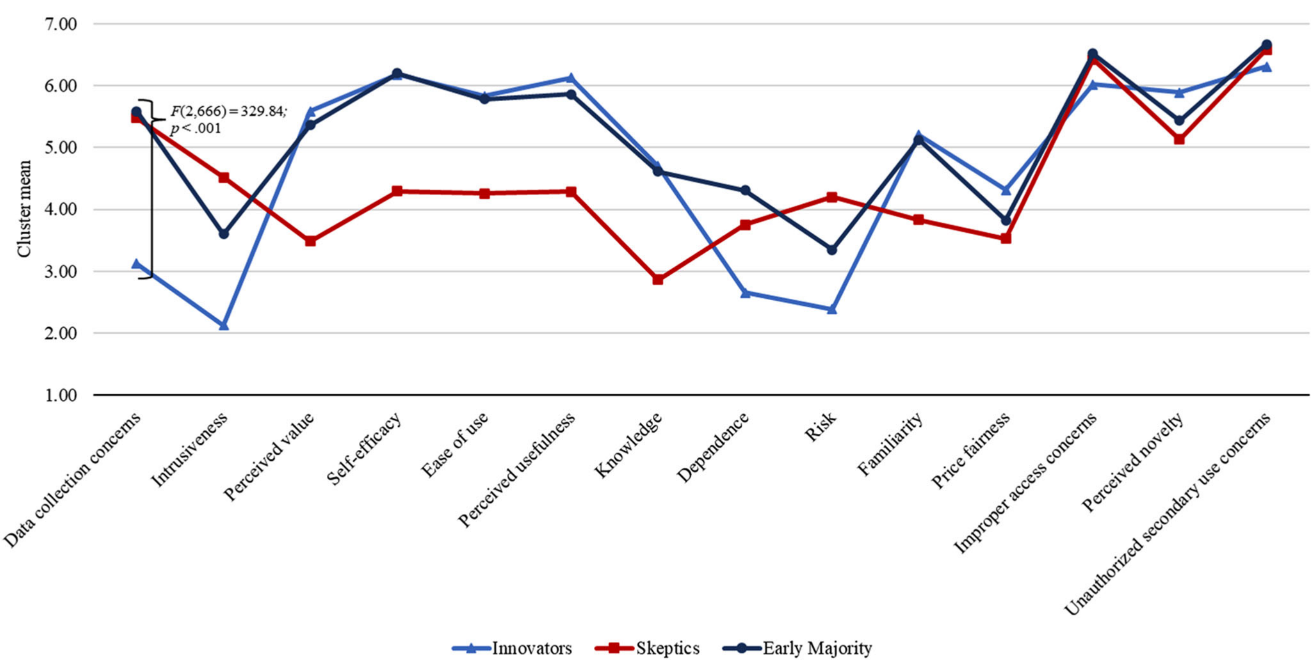

FIGURE 1 Factors pro and against the adoption of AI technologies

Thompson & Siamagka, 2022), we address privacy inhibitors as they relate to explaining AI algorithms. With this novel approach, we conceive of and empirically test mechanistic explanations of AI algorithms as a crucial inhibitor and thereby demonstrate that providing consumers with these explanations significantly reduces their data collection concerns. We also establish the most appropriate level of explanatory detail to share with consumers to reduce their concerns. Second, we specify the psychological process by which providing mechanistic explanations inhibits data collection concerns, revealing a novel mediating mechanism that pertains to consumers' subjective understanding of how AI algorithms work (Cadario et al., 2021). As we show, for the first time, detailed mechanistic explanations decrease data collection concerns, because consumers understand better how AI algorithms gather and use their data to provide outputs (e.g., recommendations). Third, in addition to privacy concerns as barriers to AI technology adoption, with indirect effects on consumers' intentions to buy and use related offerings (Huang & Qian, 2021; Mariani et al., 2022; Park et al., 2021), we detail the direct relationship by which reducing data collection concerns can encourage the adoption of AI technologies. Based on these theoretical contributions, we derive relevant practical ideas for encouraging the diffusion of AI technologies. Companies can use our findings to design strong communication strategies that reduce the perceived opacity of AI algorithms, decrease data collection concerns, and enhance the adoption of AI technologies.

2 | CONCEPTUAL FOUNDATIONS AND HYPOTHESES

Research into data collection concerns investigates various AI-driven marketing contexts, including recommendation systems, personalization (Martin & Murphy, 2017), e-commerce (Maseeh et al., 2021), customer service (Rajaobelina et al., 2021), and human–computer interactions (Pitardi & Marriott, 2021). The tremendous data required by all of these AI-driven ecosystems, for their development and functioning, necessarily places data collection and related concerns at the center of any discussions of AI (Davenport et al., 2019). Consumers generally do not know or understand how AI algorithms gather and use their personal data to make decisions, which leaves them worried about whether they should provide personal information (Puntoni et al., 2021; Thomaz et al., 2020). But if companies offer explanations that help consumers understand how AI algorithms work, including how their data inform outcomes (Rai, 2020)—or what we call mechanistic explanations—they might be reassured.

2.1 | Using mechanistic explanations of AI algorithms to inhibit data collection concerns

A mechanistic explanation describes how the various parts of a system work and interact to generate an outcome (Craik, 1943; Glennan, 1996). In marketing settings, mechanistic explanations often reveal how products function (Fernbach et al., 2013), by describing how the attributes or parts of a product work together to produce a certain benefit for the consumer (i.e., outcome). Accordingly, we define *mechanistic explanations of AI algorithms* as descriptions of how the parts that constitute an AI algorithm (e.g., data collection and storage, statistical and computational techniques) function, in combination, to produce and deliver relevant outcomes to consumers (e.g., recommendations). In experimental studies, mechanistic explanations of AI algorithms generate positive attitudes and behavioral intentions toward related technologies, such that consumers who receive mechanistic explanations trust recommendation agents more (Wang & Benbasat, 2007), exhibit more satisfaction with algorithm-based decisions (Tomaino et al., 2020), and are more likely to use AI solutions in a health care setting (Cadario et al., 2021). Among these investigations though, we know of no studies that conceive of or test explicitly mechanistic explanations of AI algorithms as an inhibitor of data collection concerns. Prior studies also tend to contrast the presence of a mechanistic explanation against the absence of any explanation, rather than specifying the level of explanatory detail that reduces data collection concerns the most.

2.2 | Levels of detail in mechanistic explanations

Mechanistic explanations include varying levels of detail, so marketers must choose the most appropriate level when explaining a product's functioning to consumers (Fernbach et al., 2013; Rozenblit & Keil, 2002). Providing insufficiently detailed explanations can backfire because consumers perceive these minimally detailed explanations as incomplete, shallow, and unsatisfying. Consumers may devalue the insufficiently described product (Simmons & Lynch, 1991) and avoid it (Lee, 1971). A shallow explanation also forces consumers to infer missing information about how the product works, which entails greater cognitive effort and thus a form of inconvenience for consumers. Some consumers even indicate a willingness to pay more for a product that comes with a detailed explanation of its functioning (Fernbach et al., 2013). Because detailed explanations provide more complete information about product attributes, which also implies higher quality information (Keller & Staelin, 1987), consumers tend to perceive them as more meaningful and effective. They gain greater literacy, which can be especially valuable for complex services or products for which they lack domain-specific know-how (Sharma & Patterson, 1999). In the case of AI algorithms, if consumers receive less detailed mechanistic explanations, they remain subject to information asymmetry and need to exert additional cognitive effort to understand the outcomes, or else continue to bear uncertainty and risk related to using AI technologies (Puntoni et al., 2021). More detailed mechanistic explanations, because they provide complete, meaningful clarifications, thus may be more effective (André et al., 2018), in that they inform consumers how AI algorithms work and diminish data collection concerns. We thus predict:

H1: Detailed mechanistic explanations of AI algorithms reduce data collection concerns more than less detailed mechanistic explanations do.

2.3 | Facilitating subjective understanding of AI algorithms

A detailed mechanistic explanation may inhibit data collection concerns due to its ability to facilitate consumers' *subjective understanding* of how AI algorithms work. As a psychological notion, subjective understanding of a product indicates people's sense that they understand how the attributes of a product work and interact together to produce outcomes. If people do not know how a product works, they try to understand its functioning through observation (Norman, 1983), which may not be sufficient, especially if hidden or complex mechanisms cannot be identified through mere observation. In such cases, providing a mechanistic explanation can help consumers understand how the product works (Rozenblit & Keil, 2002), and detailed explanations generally enhance understanding more than less detailed versions (Fernbach et al., 2013). In decreasing perceived uncertainty, such subjective understanding should enhance product attitudes (Mitchell, 1999), including toward products that rely on AI algorithms. Consumers mostly lack in-depth expertise and perceive AI algorithms as complex and opaque, so it seems challenging, if not impossible, to understand how they gather and use data to make decisions; mere observation cannot reveal how these algorithms work either (Burrell, 2016). Therefore, if mechanistic explanations, and detailed versions in particular, enhance consumers' subjective understanding of how AI algorithms work, they should reduce concerns about providing personal data. Predicting a mediating function of subjective understanding, we thus hypothesize:

H2: Diminished data collection concerns, in response to detailed mechanistic explanations, are mediated by consumers' subjective understanding of how AI algorithms work.

2.4 | Effects of data collection concerns on AI technology adoption

If their data collection concerns diminish, consumers should be more prone to adopt AI technologies, in line with psychological ownership theory (Dittmar, 1992). People experience a sense of ownership over and connection with external objects that they perceive as their own, whether tangible (e.g., cars, laptops) or intangible (e.g., ideas, organizations). They also seek influence in decisions that affect these possessions and tend to engage in defensive behaviors if they perceive a risk of loss or access to their possessions (Pierce et al., 2001). Personal data are intangible belongings, toward which consumers feel a strong sense of ownership (Litman, 2000). If they perceive threats to this personal information, consumers also experience an undesirable state of vulnerability and risk, which pushes them to find ways to avoid exposing their data (Mattison Thompson & Siamagka, 2022). Hence, if the data collection practices seem opaque and difficult to understand, they worry more about the potential loss of ownership (Puntoni et al., 2021) and likely exhibit a reluctance to adopt AI technologies (Park et al., 2021), as a tactic to avoid such losses. If mechanistic explanations diminish consumers' data collection concerns though, they might be more likely to adopt AI technologies. Formally,

H3: Diminished data collection concerns increase the likelihood that consumers adopt AI technologies.

3 | OVERVIEW OF STUDIES

To test our predictions, we conducted four online experimental studies, between February and May 2021, recruiting US respondents through Prolific. Table 1 contains an overview of the empirical studies; Figure 2 depicts the relationships tested in each study.

Studies 1a and 1b provide tests of H1, while accounting for respondents' control over their personal data, which represents a “must-have” inhibitor of data collection concerns (e.g., Xu et al., 2012). With Study 1a, we determine the effects of three levels of explanatory detail contained in mechanistic explanations (no, less detailed, detailed) on data collection concerns, while allowing participants to infer their level of control. In Study 1b, with two levels of explanatory detail (less detailed, detailed), we test the effect of the mechanistic explanation on data collection concerns while manipulating the participants' level of control (low vs. high). Then, in Study 2, we test the prediction in H2 that subjective understanding mediates the relationship between mechanistic explanations and data collection concerns. Finally, with Study 3, we test H3 and go beyond attitudinal measures to assess a managerially relevant behavioral outcome, namely, adoption.

4 | STUDY 1 A: EFFECT OF MECHANISTIC EXPLANATIONS ON DATA COLLECTION CONCERNS

Study 1a tests whether providing consumers with detailed mechanistic explanations, compared with less detailed or no explanations, decreases data collection concerns more. It establishes that providing consumers with a detailed mechanistic explanation is necessary because less detailed and no mechanistic explanations have similar, null effects on data collection concerns. We also account for respondents' sense of control over their personal data (Table 1 and Figure 2). Study 1a includes smart bands as the empirical context, which are appropriate because they can have beneficial effects in relation to health, nutrition, and fitness and collect and aggregate extensive personal data to generate hyper-personalized recommendations.

TABLE 1 Overview of studies

Aim of each study	Variables analyzed	Empirical context	Hypotheses tested
Study 1a examines the effect of mechanistic explanations on data collection concerns. Respondents' level of control is inferred.	X: Manipulated mechanistic explanations Y: Data collection concerns	AI technologies: Top-Fit, a smart band that provides personalized healthy nutrition recommendations. Stimuli: Description of Top-Fit, explanations about how the algorithm works. Three mechanistic explanation conditions: No explanation versus less detailed explanation versus detailed explanation. Research design: between-subjects experiment. $N = 528$	H1
Study 1b examines the effects of mechanistic explanations on data collection concerns under different levels of control.	X: Manipulated mechanistic explanations Y: Data collection concerns W: Manipulated level of control	AI technologies: As in Study 1a. Stimuli: As in Study 1a, plus the description of consumers' level of control over their personal data. Two mechanistic explanation conditions: Less detailed explanation versus detailed explanation. Two control conditions: Low versus high level of control. Research design: Between-subjects experiment. $N = 367$	In further support of H1
Study 2 examines the mediating role of subjective understanding in the relationship between mechanistic explanations and data collection concerns. The high level of control is kept constant.	X: Manipulated mechanistic explanations M: Subjective understanding Y: Data collection concerns	AI technologies: As in previous studies. Stimuli: As in Study 1b. Two mechanistic explanation conditions: Less detailed explanation versus detailed explanation. High level of control. Research design: Between-subjects experiment. $N = 353$	H2
Study 3 examines the effect of data collection concerns on AI technology adoption behavior. The high level of control is kept constant.	X: Manipulated mechanistic explanations M1: Subjective understanding M2: Data collection concerns Y: Adoption behavior	AI technologies: TV-Stream, a streaming service that provides personalized movie recommendations. Stimuli: Description of TV-Stream, explanations about how the algorithm works, plus the description of consumers' level of control over their personal data. Two mechanistic explanation conditions: Less detailed explanation versus detailed explanation. High level of control. Research design: Between-subjects experiment. $N = 401$	H3

4.1 | Method

4.1.1 | Participants and study design

We recruited 528 participants (52.5% men; $M_{age} = 31.97$ years, SD = 12.00; 35.6% high school, 44.3% bachelor's degree, 15.9% master's degree, 3.6% PhD, 0.6% less than high school) to take part in a 10-min study. Participants were randomly assigned to one of the three mechanistic explanation conditions (no vs. less detailed vs. detailed).

4.1.2 | Procedure

All respondents read a passage introducing a newly released smart band, fictitiously named Top-Fit, that relies on an AI algorithm and users' personal data to generate healthy, personalized nutrition recommendations. We then prompted the respondents to engage in an imagination task, imagining that they were considering using Top-Fit to achieve a personalized healthy diet and that they had received information about how Top-Fit works. The manipulation of the three levels of explanatory detail (no vs. less detailed vs. detailed) involved both text and images

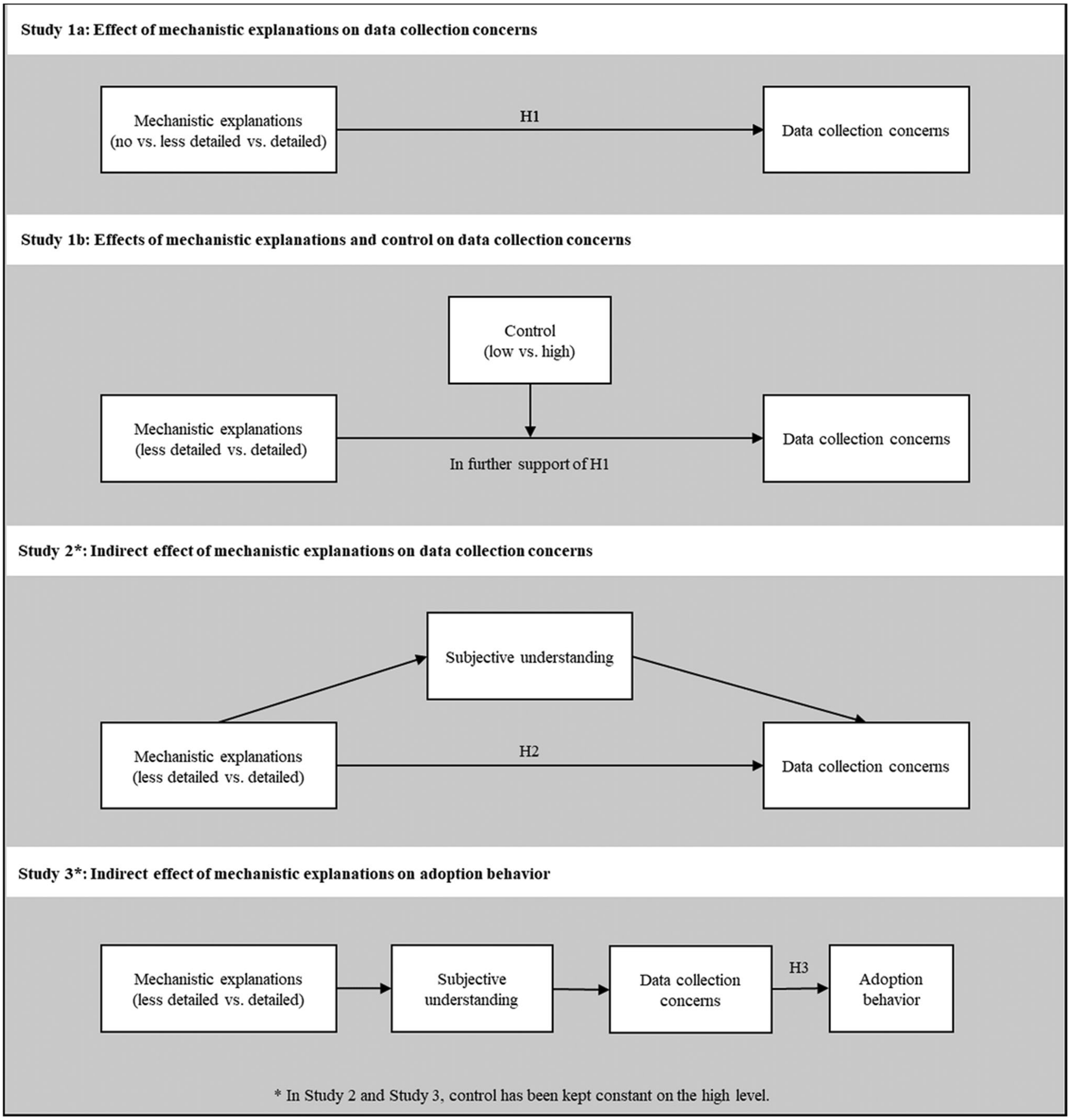

FIGURE 2 The conceptual model

(Cadario et al., 2021). The realistic stimuli were based on information retrieved from actual personal nutrition, microbiome companies' websites (e.g., DayTwo), and nutrition science studies (see Appendix B, Panel A), then reviewed and revised by an expert computer and data scientist. A pretest of the stimuli ($N = 170$) confirmed that the level of explanatory detail (i.e., extent to which the mechanistic explanation of the Top-Fit algorithm is 1 = "not at all detailed" to 7 = "very detailed") differed significantly across the three mechanistic explanation conditions ($F(2, 167) = 54.00$, $p < 0.001$, $\eta^2 = 0.39$). According to planned contrasts with Bonferroni multiple-comparison correction, pretest participants believed that the explanation was more detailed in the detailed mechanistic explanation condition ($M_{det} = 6.19$; $SD = 0.93$) compared with the less detailed ($M_{lessdet} = 4.88$; $SD = 1.34$, $F(1, 167) = 28.60$, $p < 0.001$) or no ($M_{no} = 3.63$; $SD = 1.59$, $F(1, 167) = 107.96$, $p < 0.001$) mechanistic explanation conditions; also, they perceived the mechanistic explanation as more detailed in the less detailed condition than in the no explanation condition ($F(1, 167) = 25.67$, $p < 0.001$).

In the main study, after being exposed to the stimuli reflecting one of the three mechanistic explanation conditions, participants rated their data collection concerns (three-item, 7-point Likert scale, e.g., "I am concerned that Top-Fit collects too much personal, clinical, and nutritional information about me," 1 = "strongly disagree," 7 = "strongly agree"). Then, participants expressed their perceptions of a set of constructs that also might affect data collection concerns: Perceived control over their personal data ("I perceive that the level of control I would have over the management of the personal, clinical, and nutritional information I would provide to Top-Fit would be…," 1 = "very low," 7 = "very high"), familiarity with AI technologies and AI algorithms ("I consider myself familiar with AI products and services/algorithms," 1 = "strongly disagree," 7 = "strongly agree"), perceived susceptibility to health diseases ("Relative to an average person of my same age and gender, I consider myself to be at risk of health disease related to bad nutrition," 1 = "much lower," 7 = "much higher"), and perceived self-efficacy for nutrition ("In general, I feel that I am confident in my ability to decide whether a certain food is good for me," 1 = "not at all confident," 7 = "extremely confident") (see Appendix C for the measurement scales and their properties; see Appendix D, Panel A, for the justifications of using the selected covariates). To avoid priming effects, following the imagination task, we randomly assigned a separate group of respondents ($N = 240$) to one of the three mechanistic explanation conditions and asked them to indicate their perceptions of the level of detail, as a manipulation check. Finally, all respondents provided demographic information.

4.2 | Results

4.2.1 | Manipulation check

The manipulation of the level of detail of the mechanistic explanation was successful. Respondents perceived the three mechanistic explanations as different in their explanatory detail ($F(2, 237) = 30.05$, $p < 0.001$, $\eta^2 = 0.20$). Planned contrasts, with Bonferroni multiple-comparison correction, confirmed that respondents in the more detailed condition perceived the mechanistic explanation as more detailed ($M_{det} = 5.92$; SD = 1.00) than those in the less detailed condition ($M_{lessdet} = 5.20$; SD = 1.65, $F(1, 237) = 8.68$, $p = 0.01$). Respondents in the less detailed condition also perceived the mechanistic explanation as more detailed than those in the no mechanistic explanation condition ($M_{no} = 4.03$; SD = 1.88, $F(1, 237) = 22.76$, $p < 0.001$).

4.2.2 | Test of covariates' assumptions

Before testing H1, we checked for the assumptions of analysis of covariance (ANCOVA). Only perceived control met the assumptions (see Appendix D, Panels B and C), so we included it as a covariate in the model.

4.2.3 | Direct effects

To assess the effect of different levels of mechanistic explanation detail on data collection concerns, we applied a one-way ANCOVA to the between-subjects design with three levels, with perceived control as a covariate. The results reveal that a mechanistic explanation (0 = no; 1 = less detailed; 2 = detailed) has a significant effect on data collection concerns ($F(2, 284) = 15.02$, $p < 0.001$, $\eta^2 = 0.10$), along with a significant effect of perceived control ($F(1, 284) = 24.41$, $p < 0.001$). Planned contrasts, with Bonferroni multiple-comparison correction, further confirm that the level of data collection concerns decreases significantly as the level of explanatory detail increases, such that a detailed mechanistic explanation diminishes data collection concerns more ($M_{det} = 3.06$; SD = 1.64) than a less detailed mechanistic explanation ($M_{lessdet} = 4.05$; SD = 1.41, $F(1, 284) = 17.71$, $p < 0.001$) or no mechanistic explanation ($M_{no} = 4.24$; SD = 1.58, $F(1, 284) = 26.61$, $p < 0.001$). Notably, the effects of less detailed and no mechanistic explanations on data collection concerns do not differ significantly ($F(1, 284) = 0.85$, $p = 1.00$). Overall, the results of Study 1a support H1: Detailed mechanistic explanations of AI algorithms reduce data collection concerns more than less detailed versions, but the effects of less detailed and no mechanistic explanations on data collection concerns are not significantly different. These effects account for respondents' inferred control over their personal data.

5 | STUDY 1B: EFFECTS OF MECHANISTIC EXPLANATIONS AND CONTROL ON DATA COLLECTION CONCERNS

Study 1b builds on Study 1a in two ways. First, considering the findings of Study 1a that the effects of less detailed and no mechanistic explanations on data collection concerns are not significantly different, Study 1b focuses on just two conditions: Less detailed versus detailed. Second, in Study 1a, control over consumers' personal data was inferred; in Study 1b, we manipulate the level of control, to enhance the robustness of the effect of mechanistic explanations on data collection concerns. Thus, Study 1b tests the effect of detailed (vs. less detailed) mechanistic explanations on data collection concerns when respondents have high (vs. low) levels of control (Table 1 and Figure 2).

5.1 | Method

5.1.1 | Participants and study design

We recruited 367 participants (51% men; $M_{age} = 35.93$ years, SD = 13.74; 34.1% high school, 41.7% bachelor's degree, 19.9% master's degree, 3% PhD, 1.3% less than high school) to take part in a 10-min study. They were randomly assigned to a 2 (mechanistic explanations: less detailed vs. detailed) × 2 (control: low vs. high) between-subjects design.

5.1.2 | Procedure

All participants read the description of Top-Fit and were prompted to engage in the imagination task from Study 1a. We manipulated the mechanistic explanation of AI algorithms at two levels (less detailed vs. detailed) and control at two levels (low vs. high). The stimuli for mechanistic explanations were the same as in Study 1a. The stimuli for control came from Martin et al. (2017); participants in the low control condition read that they would not have full control over their personal, clinical, and nutritional information (e.g., Top-Fit could decide to store some personal data in its backup systems, despite users' preference to delete them), whereas participants in the high control condition learned they kept full control (e.g., they could decide at any time which information to delete from Top-Fit's backup systems) (see Appendix B, Panel A). Respondents were randomly assigned to one of the four conditions.

Thereafter, participants in each condition provided their data collection concerns and rated the covariates: Familiarity with AI technologies and algorithms, perceived susceptibility to health diseases, and perceived self-efficacy for nutrition, measured as in Study 1a (see Appendix C). As a manipulation check, we asked respondents about their perceptions of control ("I perceive that the level of control I would have over the management of the personal, clinical, and nutritional information I would provide to Top-Fit would be...," 1 = "very low," 7 = "very high"). The manipulation check for the level of mechanistic explanation detail, as in Study 1a, involved a separate group of respondents ($N = 101$), to avoid priming effects. Finally, all respondents provided demographic information.

5.2 | Results

5.2.1 | Manipulation checks

Both manipulations were successful. Respondents in the detailed mechanistic explanation condition regarded the explanation as more detailed ($M_{det} = 6.20$, SD = 0.83) than those in the less detailed condition ($M_{lessdet} = 5.57$, SD = 1.20; $t(99) = -3.06$, $p = 0.003$). Respondents in the high control condition also perceived higher levels of control ($M_{highcontrol} = 4.72$, SD = 1.41) than those in the low control condition ($M_{lowcontrol} = 3.45$, SD = 1.59; $t(264) = -6.88$, $p < 0.001$).

5.2.2 | Test of covariates' assumptions

We checked for ANCOVA assumptions and found that only perceived susceptibility to health diseases and perceived self-efficacy for nutrition met the assumptions (see Appendix D, Panels B and C), so we included them as covariates in the model.

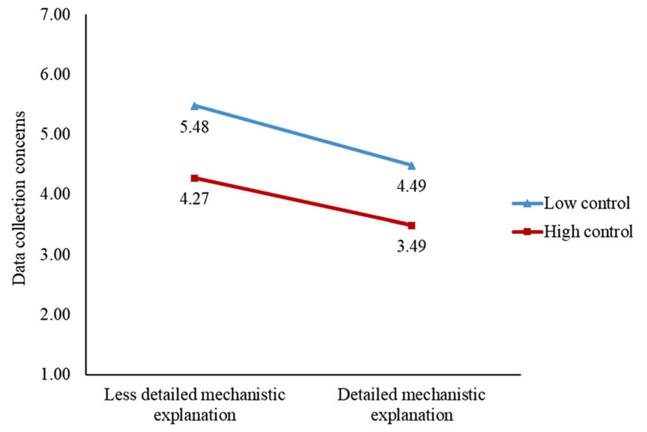

FIGURE 3 Effects of mechanistic explanations and control on data collection concerns

5.2.3 | Conditional direct effects

We tested the predictions using a between-subjects ANCOVA with data collection concerns as the dependent variable, mechanistic explanation (0 = less detailed; 1 = detailed) as an independent variable, control (0 = low; 1 = high) as a moderator, and perceived susceptibility to health diseases and perceived self-efficacy for nutrition as covariates. The results, in Figure 3, suggest a significant main effect, such that the mean level of data collection concerns reported by respondents in the detailed mechanistic explanation conditioni ($M_{det} = 4.00$, $SD = 1.78$) is significantly lower than that reported by respondents in the less detailed mechanistic explanation condition ($M_{lessdet} = 4.91$, SD = 1.66; $F(1, 260) = 20.55$, $p < 0.001$, $\eta^2 = 0.07$). We also find a significant main effect of control; the mean level of data collection concerns reported by respondents in the high control condition ($M_{highcontrol} = 3.87$, SD = 1.81) is significantly lower than that in the low control condition ($M_{lowcontrol} = 4.98$, SD = 1.57; $F(1, 260) = 26.58$, $p < 0.001$, $\eta^2 = 0.09$). Furthermore, the mechanistic explanation × control interaction is not significant ($F(1, 260) = 0.29$, $p = 0.59$, $\eta^2 = 0.001$), confirming the crucial role of the detailed mechanistic explanation, beyond the effects of consumers' control. Planned contrasts, with Bonferroni multiple-comparison correction, reveal that the detailed mechanistic explanation reduces data collection concerns more than the less detailed mechanistic explanation in both high control ($M_{lessdet} = 4.27$, SD = 1.71; $M_{det} = 3.49$, SD = 1.84; $F(1, 260) = 7.63$, $p = 0.01$) and low control ($M_{lessdet} = 5.48$, SD = 1.39; $M_{det} = 4.49$, $SD = 1.59$; $F(1, 260) = 13.38$, $p < 0.001$) conditions. These effects arise along with significant effects of perceived susceptibility to health diseases ($F(1, 260) = 10.53$, $p = 0.001$) and perceived self-efficacy for nutrition ($F(1, 260) = 14.08$, $p < 0.001$).

The findings thus provide further support for H1. Detailed mechanistic explanations of AI algorithms reduce data collection concerns more than less detailed mechanistic versions, across various levels of control that consumers have over their personal data. The findings also corroborate the relevance of detailed mechanistic explanations as crucial inhibitors of data collection concerns: They decrease data collection concerns even when control is low.

6 | STUDY 2: MEDIATION OF SUBJECTIVE UNDERSTANDING BETWEEN MECHANISTIC EXPLANATIONS AND DATA COLLECTION CONCERNS

To build on these findings, in Study 2 we investigate the process underlying mechanistic explanation effects, including the potential mediation by consumers' subjective understanding of how AI algorithms work. Noting the significant effect of control that emerged in Study 1b, in Study 2 we keep the level of control constant and high across mechanistic explanation conditions (Table 1 and Figure 2).

6.1 | Method

6.1.1 | Participants and study design

We recruited 353 participants (57.8% men; $M_{age} = 33.63$ years, $SD = 10.90$; 29.2% high school, 43.9% bachelor's degree, 24.6% master's degree, 1.4% PhD, 0.9% less than high school) to take part in a 10-min study. They were randomly assigned to one of the two mechanistic explanation conditions (less detailed vs. detailed).

6.1.2 | Procedure

The Top-Fit description and imagination task were the same as in previous studies. The control levels remained constant and high, and the two mechanistic explanation conditions featured the stimuli from Study 1b (Appendix B, Panel A). After being exposed to the stimuli, respondents completed measures of their subjective understanding of how AI algorithms work (three-item, 7-point Likert scale, e.g., "I have clearly understood how Top-Fit's algorithm elaborates personal, clinical, and nutritional data," 1 = "strongly disagree," 7 = "strongly agree"). They also indicated their data collection concerns and rated the covariates and manipulation check for perceived control, using the measures from Study 1b (Appendix C). A separate group of respondents ($N = 160$) rated the perceived level of mechanistic explanation detail for that manipulation check. Finally, all respondents provided demographic information.

6.2 | Results

6.2.1 | Manipulation checks

The manipulation of mechanistic explanation was successful: Respondents in the detailed condition perceived the explanation as more detailed ($M_{det} = 6.10$, $SD = 0.96$), compared with those in the less detailed condition ($M_{lessdet} = 5.11$, $SD = 1.68$; $t(158) = -4.55$, $p < 0.001$). The control level also was correctly perceived as high, with values significantly above the scale midpoint (4) ($M = 4.90$, $SD = 1.44$; $t(192) = 8.62$, $p < 0.001$).

6.2.2 | Test of covariates' assumptions

Before testing H2, we checked the ANCOVA assumptions and found that familiarity with AI technologies and algorithms, age, and perceived susceptibility to health diseases met the assumptions (see Appendix D, Panels B and C). Thus, we included these covariates in the model.

6.2.3 | Mediation analysis

In a one-way ANCOVA of the effect of mechanistic explanations (0 = less detailed; 1 = detailed) on data collection concerns, with perceived susceptibility to health diseases as covariate, we find significant effects. The mean level of data collection concerns reported by respondents exposed to the detailed mechanistic explanation condition ($M_{det} = 3.55$, $SD = 1.71$) is significantly lower than that reported by respondents exposed to the less detailed mechanistic explanation condition ($M_{lessdet} = 4.12$, $SD = 1.61$; $F(1, 190) = 6.18$, $p = 0.01$, $\eta^2 = 0.03$). We note a significant effect of perceived susceptibility to health diseases ($F(1, 190) = 8.06$, $p = 0.01$).

To assess the variables that might explain the relationship between mechanistic explanations and data collection concerns, we used a simple mediation model with confidence intervals (CIs) and 5000 bootstrap iterations (Hayes, 2018; PROCESS model 4), in which subjective understanding is the mediator, and familiarity with AI technologies and algorithms, perceived susceptibility to health diseases, and age are covariates. The results indicate a significant indirect effect of mechanistic explanations on data collection concerns, through subjective understanding ($b_{indirect} = -0.21$, 95% CI: −0.42 to −0.05), along with significant effects of familiarity with algorithms ($b = 0.17$, 95% CI: 0.03 to 0.30), and perceived susceptibility to health diseases ($b = 0.20$, 95% CI: 0.06 to 0.34). After accounting for this indirect effect, the direct effect of mechanistic explanations on data collection concerns is no longer significant ($b_{direct} = -0.35$, 95% CI: −0.81 to 0.12). That is, the detailed mechanistic explanation increases consumers' subjective understanding (path a; $b = 0.50$, $p = 0.003$), which reduces their data collection concerns (path b; $b = -0.42$, $p < 0.001$) (see Appendix E, Panel A, for further details). These results support H2: Mechanistic explanations reduce consumers' data collection concerns through the mediation effect of greater subjective understanding of how AI algorithms work.

7 | STUDY 3: EFFECT OF DATA COLLECTION CONCERNS ON ADOPTION BEHAVIOR

Study 3 complements Studies 1a-2 in two ways. First, we test whether reduced data collection concerns increase the likelihood that consumers adopt AI technologies, such that we move beyond attitudinal measures to include actual behavioral outcomes. Second, we investigate a different category of AI technologies, television streaming services, that tracks extensive but less sensitive personal data, thus helping enhance the findings' external validity. Consumers' level of control over their data remains constant and high across mechanistic explanation conditions (Table 1 and Figure 2).

7.1 | Method

7.1.1 | Participants and study design

We recruited 401 participants (52.4% men; $M_{age} = 36.94$ years, $SD = 13.92$; 39.9% high school, 40.4% bachelor's degree, 15% master's degree, 3.5% PhD, 1.2% less than high school) to take part in a 10-min study. They were randomly assigned to one of the two mechanistic explanation conditions (less detailed vs. detailed).

7.1.2 | Procedure

All respondents read a passage introducing a new streaming service, fictitiously named TV-Stream, equipped with an AI algorithm that would leverage users' personal data to provide personalized movie recommendations. The task for Study 3 required participants to imagine they were considering whether to subscribe to TV-Stream and had received information about how it works. The mechanistic explanation manipulation featured both text and images (Cadario et al., 2021) and described the mechanism by which the AI algorithm derived personalized movie recommendations. The realistic stimuli (see Appendix B, Panel B) contained information retrieved from the websites of leading subscription-based streaming service providers (e.g., Netflix Help Center) and scientific reports about streaming service recommendation systems affirmed by an expert computer and data scientist. The pretest for these stimuli ($N = 101$) confirmed that the mechanistic explanations differed significantly in their level of detail ($t(99) = -2.90$, $p = 0.01$); the detailed version was perceived as more detailed ($M_{det} = 6.29$, SD = 0.67) than the less detailed one ($M_{lessdet} = 5.84$, SD = 0.89).

After reviewing the stimuli, participants in each condition rated their subjective understanding of how the TV-Stream algorithm works, their data collection concerns, and their likelihood of subscribing (clicking a button to proceed with the subscription or not). Then, participants expressed their perceptions of a set of constructs that also might affect data collection concerns, subjective understanding, and adoption behavior: Familiarity with AI technologies and algorithms, interest in movies, perceived self-efficacy for movie choice, and current streaming service subscription status. Finally, the respondents completed the manipulation checks for perceived control and mechanistic explanation, though again, the latter check relied on a separate group of respondents ($N = 105$) to avoid priming effects. The behavioral choice to subscribe or not was measured as a dichotomous variable (0 = "no subscription," 1 = "subscription"); all other constructs were measured as in previous studies but adapted to a television streaming service context (see Appendix C for the measurement scales and their properties; see Appendix D, Panel A, for the justification of using the selected covariates). Finally, all respondents provided demographic information.

7.2 | Results

7.2.1 | Manipulation checks

The mechanistic explanation manipulation was successful, such that respondents in the detailed condition perceived the explanation as more detailed ($M_{det} = 6.23$, SD = 0.96) than those in the less detailed condition ($M_{lessdet} = 5.40$, SD = 1.25; $t(103) = -3.84$, $p < 0.001$). Also, the control level was correctly perceived as high (>scale midpoint of 4) ($M = 4.79$, SD = 1.46; $t(295) = 9.29$, $p < 0.001$).

7.2.2 | Test of covariates' assumptions

Before testing H3, we checked for both ANCOVA and logit binary regression assumptions. Familiarity with AI technologies and algorithms, interest in movies, perceived self-efficacy for movie choice, current streaming service subscription status, gender, and age met either ANCOVA's or logit binary regression's assumptions (see Appendix D, Panels C and D). Therefore, we included these covariates in the model.

7.2.3 | Mediation analysis

To test our prediction, we used the PROCESS syntax to design the model in Figure 2, Study 3. With CIs and 5000 bootstrap iterations, we assessed the variables that we predicted would explain the relationship between mechanistic explanations and adoption behavior (0 = no subscription; 1 = subscription), with familiarity with AI technologies and algorithms, interest in movies, perceived self-efficacy for movie choice, current streaming service subscription status, gender, and age as covariates. The results indicate a significant, serial, indirect effect of mechanistic explanations on adoption behavior through subjective understanding and data collection concerns ($b_{indirect} = 0.08$, 95% CI: 0.02 to 0.16), along with significant effects of familiarity with AI technologies (on subjective understanding $b = 0.11$, 95% CI: 0.01 to 0.20; on adoption $b = 0.29$, 95% CI: 0.02 to 0.56), familiarity with algorithms (on subjective understanding $b = 0.16$, 95% CI: 0.07 to 0.26), interest in movies (on data collection concerns $b = -0.25$, 95% CI: −0.38 to −0.12; on adoption behavior $b = 0.28$, 95% CI: 0.09 to 0.47), and age (on data collection concerns $b = 0.02$, 95% CI: 0.004 to 0.03). Specifically, mechanistic explanations predict subjective understanding of how AI algorithms work (path a; $b = 0.34$, $p = 0.003$), which predicts data collection concerns (path d; $b = -0.57$, $p < 0.001$), and the latter then decrease adoption behavior (path b; $b = -0.39$, $p < 0.001$) (see Appendix E, Panel B, for further details). These results support H3 and confirm the findings of our previous studies in a different product setting. Furthermore, we determine that diminished data collection concerns, linked to detailed mechanistic explanations, can be explained by an indirect effect, such that a stronger subjective understanding of how AI algorithms work reduces data collection concerns. Then, this reduced level of data collection concerns increases the likelihood that consumers adopt AI technologies.

8 | GENERAL DISCUSSION

Even as they spread and gain greater capacities, consumers remain reluctant to embrace AI technologies in the products and services they buy, seemingly due to their data collection concerns (Cisco, 2019; Insider Intelligence, 2020). A clear understanding of the factors that might lower these concerns thus is crucial for encouraging the diffusion of AI technologies. Greater consumer control is clearly required (Martin & Murphy, 2017; Xu et al., 2012), which is why we carefully account for it, but we also conceptually predict an additional, crucial inhibitor: Mechanistic explanations of AI algorithms. As we empirically demonstrate, mechanistic explanations decrease data collection concerns across different levels of control, regardless of whether a control is inferred by consumers (Study 1a) or explicitly communicated by the company as high or low (Study 1b). We also clarify how this diminished effect takes place: Detailed mechanistic explanations increase consumers' subjective sense that they understand how the AI algorithm works, which reduces their data collection concerns (Study 2). Finally, we establish downstream effects of reducing data collection concerns, including greater adoption of AI technologies (Study 3).

8.1 | Theoretical implications

With these findings, we build on investigations of consumers' privacy and data collection concerns (Cloarec et al., 2022; Maseeh et al., 2021) and identify new ways to overcome them (Martin & Murphy, 2017; Martin et al., 2017; Mattison Thompson & Siamagka, 2022). Our novel empirical evidence that mechanistic explanations can inhibit data collection concerns represents a response to calls for further insights into consumers' responses to AI algorithms that collect and use their personal data to provide personalized recommendations (Mariani et al., 2022). Consumers tend to perceive AI technologies as opaque (Burrell, 2016), such that they avoid disclosing personal data (Puntoni et al., 2021; Thomaz et al., 2020), but a detailed explanation that reveals how AI algorithms work can decrease such concerns. Our conceptualization also builds on recent research that proposes mechanistic explanations of products (Fernbach et al., 2013) and AI algorithms (Cadario et al., 2021; Tomaino et al., 2020) as antecedents of positive attitudes and behavioral intentions. First, we propose a mechanistic explanation as a crucial inhibitor of data collection concerns, and second, we clarify the (high) level of explanatory detail needed to reduce data collection concerns.

Furthermore, we raise the veil on subjective understanding as to the psychological mechanism that explains the relationship between mechanistic explanations and data collection concerns. Prior literature that investigates the direct effects of inhibitors (i.e., control) on data collection concerns (e.g., Dinev & Hart, 2004; Xu et al., 2012) has not specified any such psychological processes, and, to the best of our knowledge, no previous study has conceived of or empirically tested any psychological processes of the effect of mechanistic explanations on data collection concerns. As a novel contribution, we indicate mediation by consumers' subjective understanding of how AI algorithms work, which is theoretically relevant because it helps explain the effectiveness of providing consumers with detailed mechanistic explanations. When consumers receive detailed mechanistic explanations, they understand better how AI algorithms collect and process their personal data, which helps them recognize the utility of providing such data to inform the technologies.

Finally, we contribute insights about the adoption of AI technologies specifically, not just technology adoption in general (Mariani et al., 2022). Most studies that investigate the adoption of AI solutions (Mani & Chouk, 2018), including those that cite privacy concerns as a barrier (Huang & Qian, 2021; Park et al., 2021), measure behavioral intentions rather than actual behavior and test for psychological mechanisms underlying the relationship between privacy concerns and consumers' intentions to adopt. We contribute, theoretically and empirically, by providing a conceptualization of data collection concerns as a barrier to AI technology adoption, by leveraging the concept of psychological ownership of personal data (Litman, 2000), and then testing the effect of such concerns on consumers' actual behavior. Diminished data collection concerns increase the adoption of AI technologies.

8.2 | Managerial implications

Both scholars (Rai, 2020) and practitioners (Bhalla, 2020) suggest the need to find new inhibitors of data collection concerns, as exemplified by actions adopted by Google and the European Union (Skiera et al., 2022). The results of our study offer further, more detailed, and practical insights into how practitioners can decrease data collection concerns and spread the diffusion of AI technologies: They should offer detailed mechanistic explanations, which decrease data collection concerns significantly, whether consumers have high or low levels of control over their data. If practitioners explain how their AI algorithms work, it can help consumers understand how the algorithms produce beneficial outcomes for them and diminish their data collection concerns. They must offer significant detail in these explanations, because only detailed mechanistic explanations, compared with less detailed versions, effectively decrease consumers' concerns. Consumers regard detailed explanations as more complete and meaningful, but less detailed mechanistic explanations are not any more effective for reducing data collection concerns than the absence of any explanation at all.

A real-world example helps clarify this insight: The communication strategies adopted by AI technology brands (e.g., Fitbit, DayTwo, Netflix) rarely include detailed mechanistic explanations. Rather, they highlight the outcomes or benefits offered by the algorithm (e.g., more tailored services that better meet consumers' needs). The available explanations generally are limited and fragmented. But our results suggest that this strategy is suboptimal because less detailed mechanistic explanations do nothing to address consumers' data collection concerns, relative to no mechanistic explanation at all. Google offers a notable counterpoint, in that it provides its business-to-business customers with a tool that explains, in a detailed, easy-to-understand way, how its AI algorithms work to produce certain outcomes (Kelion, 2019). Will a similar strategy pay off for firms targeting consumers too? Our results indicate it will, in that consumers are likely to exhibit decreased data collection concerns and a greater likelihood of adopting AI technologies when they have access to detailed mechanistic explanations.

On a related note, we suggest that practitioners should continue providing consumers with high levels of control, even as they implement more detailed mechanistic explanations. Although our findings suggest no significant interactions between control and mechanistic explanations, their simultaneous occurrence likely produces the lowest level of data collection concerns and thus the highest likelihood of adoption.

8.3 | Limitations and further research

Some limitations of this study provide avenues for continued research. First, to define the clusters of our preliminary study, we selected variables that previous research has identified as functional or psychological barriers to adopting AI technologies (e.g., Laukkanen, 2016; Mani & Chouk, 2018). However, other factors, such as invasion of privacy, trust, or deception (e.g., Malhotra et al., 2004) may define consumer clusters. We invite researchers to apply these variables when investigating the adoption of AI technologies.

Second, our experimental approach establishes some degree of generalizability, because we conducted the experiments in different empirical contexts (smart band and streaming service). For further external validity, additional studies might test our hypotheses using other empirical contexts, platforms, or types of data (Scarpi et al., 2022).

Third, the experimental approach helps establish causality and high levels of internal validity; we used fictitious brands to avoid potentially confounding influences of brand attitudes or familiarity. But in reality, self-brand connections and the brand concept might affect consumers' adoption of AI technologies (Casidy et al., 2021). These brand-related factors then might moderate the effect of mechanistic explanations on data collection concerns and the adoption of AI technologies. Continued research should explore these influences.

Fourth, the experimental protocol uses realistic imagination tasks. Although the respondents may have not encountered or heard about the AI technologies presented in the experimental scenarios. Similarly, our experimental studies took place online, which is not per se a limitation—the adoption of many AI technologies occurs online (e.g., subscribing to TV streaming service providers)—but we acknowledge that the shopping experience and related data collection concerns may differ if the consumer shops online or in stores. Research that features real shopping contexts could address both these latter limitations and further corroborate our findings.

Fifth and finally, our empirical studies involve US respondents. Cultural dimensions may affect information disclosure attitudes, intentions to adopt AI technologies, and willingness to seek and give information about these technologies in offline and online contexts. Continued research might test the relationships hypothesized in this study in a cross-cultural context.

In conclusion, expanding the mainstream diffusion of AI technologies requires reducing consumers' data collection concerns, which in turn requires research that can identify their inhibitors. With this study, we show that “details matter.” When consumers receive detailed mechanistic explanations (in addition to high levels of control), they understand better how AI algorithms work, which decreases their data collection concerns and thereby promotes their adoption of AI technologies.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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