Unlocking the potential of Artificial Intelligence:

barriers and barriers' inhibitors regarding the adoption of artificial intelligence-enabled products by consumers

PhD dissertation

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Introduction

In the past decade, market forecasts (ABI Research, 2014; Cisco, 2014; Ericsson, 2010) and consulting reports (Gartner, 2018; Manyika et al., 2015) predicted that 2020 would be a breakthrough year for artificial intelligence (AI). Euphoric projections foresaw mainstream adoption of artificial intelligence-enabled products - also known as smart objects (SOs) - (e.g., autonomous vehicles, smart robots, virtual assistants, conversational platforms) and connections of an estimated 50 billion devices to the Internet. But the reality of 2020 has not lived up to these predictions; not only have AI-enabled products not spread to the mainstream (Newman, 2020), but only 20 billion connected devices are actually in use out of the 50 billion that were predicted (Kranz, 2019), suggesting that "the road to mass adoption of the smart home will likely be a long and bumpy one" (Morrissey, 2019).

Why do consumers remain reluctant to buy AI-enabled products? The key factors seemingly relate to both technological features (e.g., use complexity, value offered, risk, object intrusiveness; Hubert et al., 2019; Johnson, Kiser, Washington, and Torres, 2018; Laukkanen, 2016; Lee and Coughlin, 2015; Mani and Chouk, 2017, 2018; Ram and Sheth, 1989) and consumers' individual characteristics (e.g., data collection concerns, desire to avoid becoming dependent on AI-enabled products, low usage self-efficacy; Hsu and Lin, 2016; Johnson et al., 2018; Lee and Coughlin, 2015; Mani and Chouk, 2017, 2018; Ram and Sheth, 1989). Notably, data collection concerns (DCC), defined as consumers' concerns about how companies gather and use their personal data (Malhotra, Kim, and Agarwal, 2004; Smith, Milberg, and Burke, 1996) appear strongly influential, such that AI technologies' ability to collect and process huge amounts of highly personal data prompt consumers to avoid or delay their adoption of AI-enabled products (Berger-de Leon, Reinbacher, and Wee, 2018; Insider Intelligence, 2020). According to a recent survey, 87% of sales delays stem from consumers' privacy concerns (Cisco, 2019). That is, DCC appears to hinder purchase intentions, being a crucial concern for consumers.

Although the relevance that several market and consulting reports ascribe to DCC, no empirical evidence so far has shown the actual role played by this barrier in preventing consumers' adoption of AI-enabled products. Therefore, Paper 1 identifies what are the barriers specific to the adoption of these devices and shows that DCC is the most important barrier in discriminating consumers between adopters and non-adopters of AI-enabled products. As a consequence, mainstream diffusion of AI-enabled products will require reductions in DCC, or else business efforts to neutralize or mitigate DCC's adverse effects.

Some studies suggest that granting consumers control over their personal data management (i.e., *control*) is key to inhibiting DCC (e.g., Malhotra, Kim, and Agarwal, 2004; Xu, Teo, Tan, and Agarwal, 2012), and some companies (e.g., Apple, Facebook) have implemented policies to help consumers see which information is being collected and decide whether to allow such collections or when to remove their information from a company's database. Beyond this direct effect of control on DCC, it also seems likely to interact with other relevant inhibitors, though these combined effects surprisingly have not been much studied (Aguirre, Mahr, Grewal, Ruyter, and Wetzels, 2015; Martin, Borah, and Palmatier, 2017; Martin and Murphy, 2017). For example, the quality of information that companies provide to explain how their AI-enabled products' algorithms process personal data to produce a certain outcome, or *information detail*, is critical in AI contexts (Mastercard, 2020; Puntoni, Reczek, Giesler, and Botti, forthcoming; Rai, 2020), because consumers generally lack sophisticated knowledge about how the algorithms work, which strongly feeds their DCC (Cisco, 2019). Providing consumers with detailed information about the functioning of AI-enabled products' algorithms should decrease DCC, alone and in interaction with control. Therefore, Paper 2 investigates whether, by which pathways, and in which settings the provision of detailed information combines with control to reduce DCC in an AI-enabled product domain.

All barriers we consider in Paper 1 and Paper 2 stem from either AI-enabled product technical capacities (e.g., connectivity, ubiquity, and smartness) or consumers' personal traits. Focusing on AI-enabled product capacities, they depend on both SO technical abilities (e.g., being provided with

Internet connection, sensors, AI systems) as well as human-like characteristics (e.g., usage of natural language to communicate with the user, having humanized names and genders, and ability to interact with the user in real time). The human-like characteristics enhance the AI-enabled product's social aspect, making AI-enabled product s' social presence more salient (McLean & Osei-Frimpong, 2019). This social aspect has affected how consumers interact with AI-enabled products. Indeed, consumer-smart object interactions have acquired meaning that extend beyond the utilitarian benefits stemming from AI-enabled product technical capacities, as AI-enabled product characteristics are enriched by social aspects. The motivation leading consumers to use AI-enabled products now involves this social aspect. People use these devices for social purposes such as conversation (Ammari, Kaye, Tsai, & Bentley, 2019) or having company (Gao, Pan, Wang, & Chen, 2018). These characteristics lead consumers to look at AI-enabled products as potential partners in a relationship that can be referenced to social and interpersonal relationships (Gao et al., 2018; Hoffman & Novak, 2018; Novak & Hoffman, 2019). People can compare AI-enabled products to their romantic companions (Gao et al., 2018) and also attribute to them social roles (e.g., partner, master, or servant - Schweitzer et al., 2019). As the consumer-smart object interaction evolution has implications for consumer behavior (e.g., changes in the occasions of use and type of task performed), it has also implications for consumers' resistance to the adoption of AI-enabled products. However, consumer resistance frameworks have not included the relational perspective as a barrier that can explain this phenomenon so far. In order to fully understand why a consumer rejects an AI-enabled product, it is necessary to account for reasons that may stem from consumers' perception of as AI-enabled product as potential partner in a relationship. Therefore, Paper 3 identifies the relational barriers as a new category of barriers to consumers' adoption of AI-enabled products.

In conclusion, this PhD dissertation is focused on the barriers to adoption of AI-enabled products and on the identification of factors that can inhibit the effect of such barriers on the adoption from a consumer behavior perspective. More specifically, the goal of this dissertation is threefold. First, to advance knowledge about the barriers to consumers' adoption of AI-enabled products and factors that can inhibit these barriers. Second, to provide useful suggestions and solutions that could be implemented by managers to reduce the main barrier to consumers' adoption (i.e., DCC). Third, to provide evidence about the existence of a new category of barriers: the relational barrier. In conclusion, despite limitations, this PhD dissertation aims at encouraging future research building on consumer resistance to AI-enabled products.

Overview of research papers

Paper 1

The first paper included in this dissertation, titled "Against the IoT: a multi-method examination of the barriers to the adoption of smart objects", explores the barriers to consumers' adoption of SOs and provide a detailed classification of the barriers discriminating between adopters and non-adopters.

Despite the Internet of Things (IoT) is expected to open up new business opportunities, consumers' adoption of smart objects is still limited. Extant literature has widely analyzed the barriers to consumers' adoption of innovation in general and IoT services. Conversely, it investigated the barriers to SO adoption limitedly. Therefore, the aim of this study is to investigate the specific barriers to consumers' adoption of SOs, and to identify the most relevant barriers across different consumer segments. This paper is based on a multi-method approach. In Study 1 (N = 132) we run a qualitative survey based on the critical incident technique while in Study 2 (N = 669) we present the results of cluster analysis based on an online survey. Our results reveal that despite price and value are perceived as relevant obstacles to adoption, privacy concern (collection) is the most important barrier in profiling consumers across clusters.

Paper 2

The second paper included in this dissertation, titled "Details Matter! Whether, How, and When Information about Algorithms' Functioning Reduces Data Collection Concerns in the Artificial Intelligence Era", explores the effect of some inhibitors on the DCC barrier to consumers' adoption of AI-enabled products and provide an explanation about the mechanism underlying the relationship between such inhibitors and DCC, as well as information about boundary conditions under which the effect lasts/vanishes.

Consumers' DCC, regarding how companies gather and use their personal data, can impede adoption of AI–enabled products. Prior research investigates consumers' control; this study builds on those findings by considering the effects of control in combination with the level of information detail that companies provide to explain how these products process personal data, as another potential inhibitor of data collection concerns. Therefore, the current research investigates whether, how, and when a high level of control might magnify the effect of detailed information in reducing consumers' data collection concerns. Tests of the conceptual model with four independent online experiments (combined N = 1183) confirm (1) a negative effect of information detail on consumers' data collection concerns and a significant moderating influence of control (Studies 1 and 2); (2) serial mediation by perceived communication effectiveness and subsequent understanding of the utility of providing personal data, which explains the relationship between information detail and consumers' data collection concerns (Study 3); and (3) relevant boundary conditions, pertaining to the type of benefits consumers gain (Study 4). These findings add to existing theoretical knowledge, provide actionable managerial implications, and identify avenues for further research.

Paper 3

The third paper included in this dissertation, titled ""I'm Sorry Dave, I'm Afraid I Can't Do That": Non-User Fears of Negative Social Roles in the Consumer-Smart Object Relationships", explores the barriers to consumers' adoption of SOs adopting a relational perspective and provide a detailed classification of four fears experienced by consumers that can prevent them to adopt these devices.

SOs have entered into consumers' everyday life. However, despite the great potential of smart objects, their diffusion is struggling. Models on the resistance of innovation, also applied to smart devices, have tried to explain this phenomenon. However, these models rely only on innovation or user characteristics. Smart objects capabilities, such as using natural language and interacting with the user in real-time, contribute to the capacity for these devices to elicit a social presence, become anthropomorphized by consumers and perceived as a relational partner. Since, in the interpersonal domain, people can be reluctant to engage in new intimate relationships, this paper claims that the relational potentialities of smart objects can inhibit the purchase and use. So, these aspects should be taken into account when talking about resistance. From ZMET interviews on non-users, four fears emerged, each one connected to a different smart object social role: Fear of Being Controlled (Stalker), Fear of Being Dominated (Captor), Fear of Being Subordinated (Master), Fear of Losing Self Control (Seducer). This work contributes both to the resistance literature, shedding light on a new barrier (i.e., the relational barrier), and to the smart object-consumer relationship literature, discovering new (anticipated) social roles, all negative.

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Against the IoT: a multi-method examination of the barriers to the adoption of smart objects

Introduction

Smart objects (SOs) are physical objects connected to the Internet that can interact with other objects and people, and that can collect, store, and process a huge amount of data. These actions are made by SOs with agency, autonomy, and authority (Hoffman & Novak, 2018). These characteristics entail changes in the way consumers use and interact with this kind of innovation delineating a different context compared to that of innovation in general. The Internet of Things (IoT) is expected to unlock significant market opportunities. The combined markets of the IoT is forecasted to grow to about $520B in 2021 (more than double the $235B spent in 2017 – Columbus, 2018), and the number of devices connected to the Internet has exceeded 31B in 2018 (Morelli et al., 2018).

Despite these favorable predictions, the diffusion of smart objects in the market is still in its infancy. For instance, consumers' intentions to purchase smart objects increased only by 1% in the 2015-2016 period (Björnsjö, Lovati, and Viglino, 2016).

Scholars and practitioners have increasingly ascribed this inconsistency to the occurrence of relevant adoption barriers, that is, actual (functional and psychological) obstacles that may hinder consumers' desire to adopt innovations (Berger-de Leon, Reinbacher, and Wee, 2018; Mani & Chouk, 2017, 2018). However, while extant empirical research has focused on the barriers of adopting innovation in general (Laukkanen, 2016; Laukkanen, Sinkkonen, Kivijärvi, & Laukkanen, 2007; Ram & Sheth, 1989), the investigation of the specific barriers to the adoption of smart objects has been pursued to a more limited extent (Mani & Chouk, 2017, 2018).

The present study addresses this research gap. Specifically, it aims to investigate the barriers to consumers' adoption of smart objects, and to identify the most relevant barriers across different consumer segments. In this regard, Study 1 shows the results of a qualitative study that combines the barriers identified by previous literature with those ones specific to the adoption of SOs. Second, Study 2 shows the results of a quantitative study that highlights the most relevant barriers to the adoption of SOs for different consumer segments.

Theoretical background

Recent decades have witnessed a growing body of research on the factors that foster and hinder consumers’ adoption of innovative products in general (Y. Park & Chen, 2007; Ram & Sheth, 1989) as well as of smart objects (SOs) (Hubert et al., 2019; Mani & Chouk, 2017; Shin, Park, & Lee, 2018). However, despite these studies, research that aims at identifying the elements able to suppress the barriers to consumers’ adoption of SOs is still in its infancy (André et al., 2018).

The marketing literature about how consumers respond to innovations refers to two research paradigms (Laukkanen, 2016): the innovation adoption paradigm and the resistance to innovation paradigm. The former is based on theoretical models that aim at understanding how consumers’ perception of the features of an innovation (e.g., perceived usefulness and perceived ease of use; Davis, 1989) affects whether they decide to adopt it. The main models that have allowed researchers to do so are the technology acceptance model (TAM: Davis, 1989), and the unified theory of acceptance and use of technology (UTAUT: Venkatesh, Morris, Davis, & Davis, 2003). These two models have been subsequently extended to better explain consumer behavioral intention to adopt innovations. The update results in three new models, such as TAM2 (Venkatesh & Davis, 2000), TAM3 (Venkatesh & Bala, 2008), and UTAUT2 (Venkatesh, Thong, & Xu, 2012).

The latter paradigm is based on theoretical models intended to understand what are the factors that impede consumers’ adoption of innovations. This stream of literature has its foundations in the assumption that consumers resist innovations because of the occurrence of “several barriers that paralyze their desire to adopt innovations” (Ram & Sheth, 1989, p. 7). Ram and Sheth (1989) distinguished functional barriers from psychological barriers. Functional barriers (i.e., usage, value, and risk) occur when the consumer perceives that the adoption of the innovation entails significant changes (Ram & Sheth, 1989). Psychological barriers (i.e., image and tradition) occur when the adoption of the innovation and consumers' prior beliefs are in conflict (Ram & Sheth, 1989).

Marketing scholars have recently started to use the two paradigms to explain consumers' behavioral intentions toward SOs. Specifically, the application of the above-mentioned theoretical models to the SO realm resulted in the identification of several specific factors either for or against the adoption. The fact that SOs present some peculiar features, that make them a unique type of innovation (Hoffman & Novak, 2018; Novak & Hoffman, 2019), has called for some extensions of the innovation adoption models (Davis, 1989; Venkatesh et al., 2012). Indeed, building on the original versions, several studies recently developed new adoption models that include typical SO variables (Chuah et al., 2016; Kim & Shin, 2015; Shin et al., 2018; Talukder, Sorwar, Bao, Ahmed, & Palash, 2020), such as compatibility (i.e., the ability of a device to be connected and communicate with other devices inside the smart home; Shin et al., 2018), and subcultural appeal (Kim & Shin, 2015). Research on consumers' adoption of smart products has also been conducted using a combination of different theoretical models of adoption. For instance, a framework composed by both the UTAUT2 and diffusion of innovation (DOI) (Talukder, Chiong, Bao, & Hayat Malik, 2019) allowed researchers to provide a better explanation of the adoption phenomenon, since it is seen as a blend of consumers' perception of SO characteristics and consumer innovative traits.

Concerning the literature on resistance to innovations, Mani and Chouk (2017) answered to the need of updated models by the identification of two groups of barriers determining the consumer resistance to smartwatches. The first group is composed by barriers referring to the characteristics of the SO (i.e., smartwatch); therefore, it presents barriers such as perceived usefulness, perceived novelty, perceived price, and intrusiveness. The second group is composed by barriers relating to the characteristics of the consumer; therefore, it presents barriers such as privacy concerns, dependence and self-efficacy.

Although in marketing literature both paradigms have been used separately to analyze consumer behavior toward SOs, recently researchers have started to claim and proved that the analysis of consumers' adoption of complex and multifaced innovations like IoT products calls for a combination of different theoretical frameworks, so that it is possible to capture positive and negative aspects at the same time (Hubert et al., 2019). Venkatesh et al. (2003, p. 426) already shed light on this issue arguing that: "researchers are confronted with a choice among a multitude of models and find that they must 'pick and choose' constructs across the models, or choose a 'favored model' and largely ignore the contributions from alternative models. Thus, there is a need for a review and synthesis to progress toward a unified view of user acceptance." In this vein, recent studies explained consumers' adoption of SO drawing from different frameworks and concepts in the literature, mainly referring to both adoption and perceived risk theory (Hubert et al., 2019; Wang, McGill, & Klobas, 2018). These studies show a new pathway to consumers' adoption of smart products.

This scenario depicts a fragmented literature on the barriers to consumers' adoption of SOs. The implementation of both adoption and resistance model in the SO realm resulted in a miscellaneous of factors that promote and hinder consumers' adoption, such as usability factors (Mani & Chouk, 2017; Shin et al., 2018), risk factors (Hubert et al., 2019), technical factors (e.g., intrusiveness and compatibility; Mani & Chouk, 2017; Shin et al., 2018), and consumers' personality traits (i.e., optimism, innovativeness, discomfort and insecurity; (Mulcahy, Letheren, McAndrew, Glavas, & Russell-Bennett, 2019). In this mosaic of barriers, Mani and Chouk (2018), building on Ram and Sheth's (1989) model, tested the presence of new barriers specific to the IoT service domain. They presented three main categories of barriers to the adoption of IoT services: functional, psychological and individual barriers. The first category, as in Ram and Sheth's (1989) model, covers usage, value and risk barriers. The second category is enriched with two new barriers: the technology vulnerability barrier (i.e., perceived technological dependence and technology anxiety), and the ideological barrier (i.e., skepticism). The third and new category is the ideological barrier (i.e., inertia). However, this model neglects some relevant factors that might play a role in consumer resistance to smart product. These factors refer to both the SO and the individual; speaking in terms of barriers, they refer, respectively, to functional barriers (i.e., perceived novelty and intrusiveness) and to psychological barrier (i.e., privacy concerns and self-efficacy) (Mani & Chouk, 2017).

One of the main features of SOs, i.e. one of those reflecting their “smartness”, is the ability to collect, store and share information that is present in the surrounding environment (Hernández & Reiff-Marganiec, 2014; López, Ranasinghe, Patkai, & McFarlane, 2011), and so users’ personal data. SOs constantly collect consumers’ private and sensitive information and the more users integrate SOs in their lives, the more information about them the SOs collect (K. Park, Kwak, Lee, & Ahn, 2018). Moreover, the exchange of information takes place not only from consumer to consumer but also from consumers to SOs and among SOs (Yun, Lee, & Kim, 2019). Borrowing a concept from Hoffman and Novak (2018), we can say that consumers’ personal data are collected by SOs and shared with and within the assemblage. Consumers’ concerns about the data collection made by the SO can lead the consumers themselves to restrict the way they use the SO (Novak & Hoffman, 2019). This type of concerns are not attached to SOs in an exclusive way. Indeed, privacy literature has already ascribed data collection to the primary dimensions of individuals’ concerns about organizational practices, and defined it as the individuals’ perception that and resentment about the “great quantities of data regarding their personalities, background and actions are being accumulated” (H. J. Smith, Milberg, & Burke, 1996, p. 171). Malhotra, Kim, and Agarwal (2004) adapted this seminal definition to the Internet and e-commerce context defining it “as the degree to which a person is concerned about the amount of individual-specific data possessed by others relative to the value of benefits received” (Malhotra et al., 2004, p. 338). In the marketing literature, several studies shed light on consumers’ concerns about how IoT technologies collect, store and share their personal data, as well as the quantity of data these devices can collect (Balta-Ozkan, Davidson, Bicket, & Whitmarsh, 2013; Hmielowski, Boyd, Harvey, & Joo, 2019; Novak & Hoffman, 2019; Wang et al., 2018; Worthy, Matthews, & Viller, 2016), such as information on geographical location, financial, personal health and habits. In our research the term data collection concerns (DCCs) is used to refere to the degree to which a person is concerned about the quantity of his/her personal data SOs can collect and use. Some empirical studies showed that consumers' DCCs entail negative consequences. Fore instance, consumers perceive the data collection and use that smart home devices make of their personal information as a risk (Wang et al., 2018). Moreover, their concerns affect negatively the satisfaction with digital assistants (Brill, Munoz, & Miller, 2019), while it has a positive impact on the intrusiveness of smartwatches, which in turn has a positive impact on the resistance to this kind of SOs (Mani & Chouk, 2017).

Althought these facts make consumers' concerns about the collection of their personal data an issue even more salient compared to how much it was before the beginning of the IoT era (Belanger & Xu, 2015), there are no empirical evidence, to the best of our knowledge, confirming that consumers' data collection concerns can be a barrier to consumers' adoption of SOs.

Thus, given the peculiarities of SOs, the complex and various portfolio of barriers referring to them, and some evidences about the possible presence of new barriers specific to SOs (e.g., privacy concerns barriers), a clear representation of what are the consumers' barriers to the adoption of SOs and of the characteristics – in terms of barriers and individual traits - distinguishing adopters from non-adopters of SOs is needed in order to identify what are the main barriers on which an intervention can make the difference. Therefore, our research questions are:

- *What are the barriers to consumers' adoption of SOs?*
- *What is the most important barrier preventing consumers in adopting SOs, so discriminating between adopters and non-adopters?*

Overview of studies

We answered to these research questions with two online studies. Study 1 is a qualitative study. We conduct an online survey to investigate what are the barriers to consumers' adoption of SOs. The aim of this study is to understand whether consumers experience specific new barriers in addition to the ones already identified in the literature of resistance to innovation and resistance to SOs. Study 2 is a quantitative study. We conduct an online survey to identify what is the main barrier to the adoption of SOs.

Study 1

Method

Participants. We recruited 157 respondents. Some participants were disqualified because of lack of any barrier or incompleteness of the answer. Hence, responses from 132 respondents (36% female; 54% aged 18 – 30, 27% aged 31 – 45, 14% aged 46 – 60 and 5% aged over 60; 2% lower than High School education level, 31% High School education level, 42% Bachelor Degree education level, 21% Master Degree education level and 4% PhD education level; 30% student, 44% employee, 14% self-employee, 4% unemployed, 5% retired and 3% other) were analyzed.

Procedure. The qualitative online survey was conducted using an adaptation of the critical incident technique (CIT) (e.g., Bitner, Booms, and Tetreault, 1990). Respondents were asked to recall a recent opportunity in which they could purchase a SO, but they decided on not buying it. They were asked to describe the incident and the motivations for the SO non-adoption.

Data analysis

Participants' narratives were coded in two phases, using the open-coding technique of the grounded theory (Corbin & Strauss, 1990). Firstly, we analyzed the responses of each informant at a level of analysis as close as possible to the way they were voiced by everyone. Then, we ran a second round of coding in which, bearing in mind the categories that emerged from the individual-level analysis, we conducted a cross-analysis among all the informants. This second phase aimed at identifying broader categories, resulting from the collapse and the merger of the previous ones, and overarching themes. In some cases, individuals reported more than one motivation as to why smart objects were not adopted. These responses were classified into multiple categories yielding 204 occurrences. The analysis resulted in the identification of nine main macro themes. Each theme corresponded to a specific barrier to the adoption of SOs.

Findings

From the coding, nine categories emerged. Each category represents a barrier to consumers' adoption of SOs. While some barriers we identified were already present in the marketing literature about consumers' reactions to innovations and SOs (i.e., perceived value, perceived piece, novelty, negative externalities, self-efficacy, and dependence and tradition) (Johnson, Kiser, Washington, & Torres, 2018; Laukkanen, 2016; Laukkanen et al., 2007; Mani & Chouk, 2017, 2018; Ram & Sheth, 1989; Shin et al., 2018), our analysis shed light on some new barriers, specific to the SO context (i.e., risky purchase, knowledge, and privacy concerns). Barriers' definitions, absolute frequencies, and participants' quotes are reported in Table 1.

Perceived value (n=74). When consumers experience the perceived value barrier, they do not catch the value generated by the device. Often the SO is considered useless because the consumer already owns a similar device, and this leads the consumer to postpone the purchase. The low perceived value is also represented by the low perceived quality of the attributes of the product, the perplexities regarding the quality-price ratio, and the fact that the consumer knows that she will rarely use the SO.

Perceived price (n=54). When consumers experience the perceived price barrier, they perceive the price of the SO as inadequate, too high, and not consistent with the quality and utility of the device. Also, the price evaluation is made in connection with a low perceived value of the SO. The doubts on the relationship between utility and price increase the importance of the limited budget that consumers can allocate to the SO purchase. This leads the individuals not to buy the product in order to optimize the allocation of resources.

Novelty (n=20). When consumers experience the novelty barrier, they perceive a reduced originality of SOs in absolute terms and/or in relation to previous versions or similar products. Non-differentiated functions of SOs lead to postpone the purchase because consumers prefer to wait for a model or product that represents an innovative leap. On this basis, we can say that the novelty barrier seems to be an antecedent of the perceived value barrier.

Negative externalities (n=15). Negative externalities are negative effects external to the consumer-SO relationship due to the adoption of the device. These negative effects stem from the incompatibility of the SO with respondent's lifestyle or with other devices that the respondent already owns. In this case, the consumer thinks to use the SO rarely. On this basis, we can say that he negative externalities barrier seems to be an antecedent of the perceived value barrier.

Risky purchase (n=14). When consumers experience the risky purchase barrier, they fear to make a wrong purchase regarding the functionalities of the product, the price (due to the limited budget), and the unfavorable contractual conditions.

Knowledge (n=8). When consumers experience the knowledge barrier, they have low knowledge of the SO and its characteristics at the time of purchase. The low level of knowledge is due to a lack of time that they would have dedicated to the preliminary research of information. In this case, the consumer tends to delegate the purchase decision to others who have a higher knowledge of the product.

Privacy concerns (n=7). When consumers experience the privacy concerns barrier, they feel concerned about the data that SOs collect and analyze. Specifically, they fear the possibility of being victim of attacks by hackers and companies' secondary use of personal data. This barrier also refers to consumers' concerns about the intrusiveness of SOs (i.e., their ability to enter autonomously into the users' lives).

Self-efficacy (n=7). When consumers experience the self-efficacy barrier, they have low perception of their ability to use the SO due to the awareness of being to some extent adverse to technology, or the belief that SOs are too difficult to use.

Miscellaneous (n=5). This is a residual category. It is composed of reasons of non-adoption related to the individuals' conservative personality (i.e., a personality that is adverse to innovation and against the continuous control to which technology exposes those who use it or the fear of becoming dependent on the SO). The concepts that make up this category are related to the privacy concerns barrier, in particular to the intrusive aspects of the SO, and the self-efficacy barrier.

As evidenced from the results, perceived value and perceived price are the barriers that emerged more frequently in participants' narratives. This outcome is not surprising given that Study 1 is based on the memory recall of the incident. However, other relevant reasons were reported by respondents concerning the non-adoption (e.g., risky purchase and privacy concerns). Therefore, to detect and delve into the role of specific barriers for consumer segments characterized by different levels of adoption, a quantitative study is conducted with a new group of participants. To this end, a set of measurement scales were used to identify the barriers to SO adoption.

Table 1. Qualitative excerpts organized by category.

Barrier	**Definition**	**Quote**	**Absolute frequency**
Perceived value	Consumers perceive the smart object as useless and of low value	Int. #2: "Was debating on whether I should swap my current iPhone 6 to get the new iPhone. I didn't purchase it in the end because my current phone is working fine."	74
Perceived price	Consumers perceive the price as too high and inconsistent with the functionalities of the smart object	Int. #132: "Smartwatch. I did not buy it mainly because I found it too expensive."	54
Novelty	Consumers perceive smart objects as lacking originality and innovativeness	Int. #21: "Smartwatch. Not for the price (that I think it is too high) but for the features that don't represent a breakthrough."	20
Negative externalities	Consumers perceive a mismatch between the devices they already own and the smart objects	Int. #118: "About one month ago I was going to buy a "Samsung smart fitness watch" from Amazon, but I didn't, because it was not compatible with my Samsung tablet."	15
Risky purchase	Consumers perceive the risk of a bad purchasing decision (in terms of product, spending and contractual condition terms)	Int. #58: "Alexa…but I didn't know if I could have used it in Italy"	14
Knowledge	Consumers have not enough information about smart object features at the moment of purchase	Int. #71: "We were looking for a new TV. We had a look at a Smart TV which looked good, but we didn't know much about it. We decided to collect more information about it."	8

Privacy concerns	Consumers are concerned about how smart objects may process their personal information (i.e., collection, storage and diffusion of data, intrusiveness)	Int. #122: "I have been thinking about purchasing a larger TV such as 80". However, almost all the large TVs are Smart TVs. The problem is that I want a TV to be a TV, not a device that can listen to voice commands 24/7 and one that tracks everything you do. I believe the security on TVs is not good and it is not updated. The wifi and camera (if it includes it) can easily be turned on without your knowledge."	7
Self-efficacy	Consumers' self-perception of their ability in using smart objects is low because of their cognitive technology aversion or object complexity	Int. #80: "I had the chance to have a smart device that allowed me to control heating from any room in the house or outside. I felt that this could be too complicated, and things could just go wrong."	7
Miscellaneous	- Consumers are concerned about becoming dependent on the smart objects - Consumers' conservative personality hinders the adoption of smart objects	Int. #57: "Fitbit. I didn't buy it because I thought that it could have influenced significantly my behaviors" Int. #91: "We were going to purchase a Smart TV. However, after talking to the shopping assistant, my husband realized he didn't like the Internet via a TV as he is old fashioned, and he doesn't trust the Internet at all."	5

Study 2

Method

Participants. We recruited 669 respondents (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) from Prolific participated in exchange for monetary compensation.

Procedure and data analysis. The questionnaire was composed of three sections. The first section introduced the definition of smart objects and provided some examples. In the second section, respondents were asked to recall a recent opportunity in which they could purchase a smart device, but they decided on not buying it (see Study 1 for the procedure). The third section recorded the model variables, socio-demographic data, and thanked the participants. The respondents took about 12 minutes to complete the questionnaire. Measurement scales validated by previous literature were used to measure all the constructs. Some of the scales were adapted to a smart object context. The questionnaire included latent constructs measured on seven-point Likert scales (1 = "strongly disagree" to 7 = “strongly agree”), except for perceived value and price fairness that were measured with bipolar scales (Table 2).

We conducted a two-step cluster analysis to categorize sample respondents on the basis of their responses to the clustering variables (Punj and Stewart, 1983). The initial, hierarchical cluster analysis suggested a three-cluster solution. Then we used a non-hierarchical, k-means clustering procedure (MacQuenn, 1967) to develop the three-cluster solution. It grouped respondents according to their perceptions of the main barriers to adoption (i.e., data collection concerns (DCC), intrusiveness, perceived value, self-efficacy, ease of use, perceived usefulness, knowledge, dependence, risk, familiarity, price fairness, improper access concerns, novelty, and unauthorized secondary use concerns). Individual traits (i.e., optimism, innovativeness, discomfort, and insecurity), the number and type of AI-enabled products they owned, and perceived network externalities associated with the presence of AI-enabled products were not included in the clustering procedure but were used for descriptive purposes. Analyses of variance and Bonferroni pairwise comparison tests were conducted to compare the three clusters (Table 3; Figure 1). After respondents were grouped in clusters, we labeled them according to their purchase and positive word-of-mouth (WOM) intentions.

Table 2. Cluster Analysis Measures and Descriptive Statistics

Construct	Operationalization	Measurement (Source)	Cronbach's alpha α
Data collection concerns (DCC)	1. I am concerned about threats to my personal privacy coming from AI-enabled products. 2. I am concerned about data collected by AI-enabled products without my permission. 3. I am concerned that Smart Device producers are collecting too much personal information about me. 4. It bothers me to give personal information to so many Smart Device producers.	Four 7-point items anchored by “strongly disagree” [1] and “strongly agree” [7], adapted from Hsu and Lin (2016); Mani and Chouk (2017).	α = 0.94
Intrusiveness	1. Smart Devices are intrusive. 2. Smart Devices are irritating. 3. Smart Devices are indiscreet. 4. I am not comfortable with Smart Devices. 5. Smart Devices are disturbing.	Five 7-point items anchored by “strongly disagree” [1] and “strongly agree” [7], adapted from Mani and Chouk (2017).	α = 0.90
Perceived value	The value of Smart Devices is:	Five 7-point items, anchored by “not necessary” [1] and “necessary” [7],	α = 0.89

		“boring” [1] and “exciting” [7], “not a worthwhile product” [1] and “a worthwhile product” [7], “unappiling” [1] and “appiling” [7], “common” [1] and “unique” [7]*, adapted from Kleijnen, Ruyter, and Wetzels (2007) and Voss, Spangenberg, and Grohmann (2003).	
Self-efficacy	1. I know how to use Smart Devices. 2. I am confident in my ability to understand and use Smart Devices. 3. I think I am able to operate Smart Devices although I've never used it before.*	Three 7-point items anchored by “strongly disagree” [1] and “strongly agree” [7], adapted from Mani and Chouk (2017).	α = 0.91
Ease of use	1. In my opinion, Smart Devices are easy to use. 2. In my opinion, Smart Devices are fast to use. 3. In my opinion, progress in Smart Devices is clear. 4. My interaction with Smart Devices is understandable. 5. Interacting with Smart Devices does not require a lot of my mental effort.	Five 7-point items anchored by “strongly disagree” [1] and “strongly agree” [7], adapted from Laukkanen, Sinkkonen, Kivijärvi, and Laukkanen (2007); Lu, Yao, and Yu (2005).	α = 0.90
Perceived usefulness	The value of Smart Devices is:	Seven 7-point items, anchored by “ineffective” [1] and “effective” [7], “not functional” [1] and “functional” [7], “impractical” [1] and “practical” [7], “useless” [1] and “useful” [7], “inefficient” [1] and “efficient”[7], “unproductive” [1] and “productive” [7], “not helpful” [1] and “helpful” [7], adapted from Kleijnen, Ruyter, and Wetzels (2007) and Voss, Spangenberg, and Grohmann (2003).	α = 0.95
Knowledge	1. I feel very knowledgeable about Smart Devices. 2. If I had to purchase Smart Devices today, I would need to gather very little information in order to make a wider decision.* 3. I feel very confident about my ability to tell the difference in quality among different brands of Smart Devices. 4. If a friend asked me about Smart Devices, I could give them advice about different brands.	Four 7-point items anchored by “strongly disagree” [1] and “strongly agree” [7], adapted from Smith and Park (1992).	α = 0.88
Dependence	1. I am afraid of becoming dependent on Smart Devices. 2. Smart Devices will reduce my autonomy. 3. Smart Devices will strengthen my addiction to technology. 4. I'm thinking my social life will suffer from my use of Smart Devices.	Four 7-point items anchored by “strongly disagree” [1] and “strongly agree” [7], adapted from Mani and Chouk (2017).	α = 0.81
Risk	1. There is a good chance I will make a mistake if I purchase a Smart Device. 2. Smart Device is a very risky purchase.	Two 7-point items anchored by “strongly disagree” [1] and “strongly agree” [7], adapted from	α = 0.80

		Laroche, Yang, Mcdougall, and Bergeron (2005).	
Familiarity	I find Smart Devices to be:	Tow 7-point items, anchored by "novel" [1] and "familiar" [7], "atypical" [1] and "typical" [7], adapted from Cox and Cox (2002).	α = 0.75
Price fairness	The price of Smart Devices is:	Eight 7-point items, anchored by "unfair" [1] and "fair" [7], "unreasonable" [1] and "reasonable" [7], "dishonest" [1] and "honest" [7], "unacceptable" [1] and "acceptable" [7], "not justified" [1] and "justified" [7], "unsatisfactory" [1] and "satisfactory" [7], "extremely high" [1] and "extremely low" [7], "bad value for money" [1] and "good value for money" [7 adapted from Haws and Bearden (2006).	α = 0.92
Improper access concerns	1. Smart Device producers should devote more time and effort to prevent unauthorized access to personal information. 2. Smart Device producers should take more steps to ensure that the personal information in their files is accurate.* 3. Smart Device producers should take more steps to ensure that unauthorized people cannot access personal information in their computers.	Three 7-point items anchored by "strongly disagree" [1] and "strongly agree" [7], adapted from Hsu and Lin (2016).	α = 0.79
Novelty	I find Smart Devices to be:	Tow 7-point items, anchored by "new" [1] and "old" [7], "original" [1] and "unoriginal" [7], adapted from Cox and Cox (2002).	α = 0.73
Unauthorized secondary use concerns	1. Smart Device producers should not use personal information for any purpose not specifically authorized by the user. 2. Smart Device producers should never sell personal information to other companies. 3. Smart Device producers should never share personal information with other companies unless specifically authorized to do so by the user.	Three 7-point items anchored by "strongly disagree" [1] and "strongly agree" [7], adapted from Hsu and Lin (2016).	α = 0.77
Purchase intention	1. How likely are you to purchase Smart Devices? 2. How probable is it that you will purchase Smart Devices? 3. How possible is it that you will purchase Smart Devices?	Three 7-point items, anchored by "very unlikely" [1] and "very likely" [7], "very improbable" [1] and "very probable" [7], "very impossible" [1] and "very possible" [7], adapted from Grewal, Monroe, and Krishnan (1998).	α = 0.97

Positive WOM	1. I will recommend friends to buy Smart Devices. 2. I will say good things about Smart Devices to others. 3. I bring up Smart Devices in a positive way in conversations I have with friends and acquaintances. 4. In social situations, I often speak favorably about Smart Devices.	Four 7-point items anchored by "strongly disagree" [1] and "strongly agree" [7], adapted from Arnett, German, and Hunt (2003), Harrison-Walker (2001) and Zeithaml, Berry, and Parasuraman (1996).	α = 0.94
Optimism	1. Technology gives you more freedom of mobility. 2. Products and services that use the newest. technologies are much more convenient to use. 3. You find new technologies to be mentally stimulating.	Three 7-point items anchored by "strongly disagree" [1] and "strongly agree" [7], adapted from Rojas-Mendez, Parasuraman, and Papadopoulos (2017).	α = 0.84
Innovativeness	1. You can usually figure out new high-tech products and services without help from others. 2. Other people come to you for advice on new technologies. 3. You find you have fewer problems than other people in making technology work for you. 4. You keep up with the latest technological developments in your areas of interest. 5. In general, you are among the first in your circle of friends to acquire new technology when it appears.	Five 7-point items anchored by "strongly disagree" [1] and "strongly agree" [7], adapted from Rojas-Mendez, Parasuraman, and Papadopoulos (2017).	α = 0.91
Discomfort	1. Sometimes, you think that technology systems are not designed for use by ordinary people. 2. It is embarrassing when you have trouble with a high-tech gadget while people are watching.* 3. Technology always seems to fail at the worst possible time. 4. Many new technologies have health or safety risks that are not discovered until after people have used them. 5. There is no such thing as a manual for a high-tech product or service that is written in plain language. 6. If you buy a high-tech product or service, you prefer to have the basic model over one with a lot of extra features.	Six 7-point items anchored by "strongly disagree" [1] and "strongly agree" [7], adapted from Rojas-Mendez, Parasuraman, and Papadopoulos (2017).	α = 0.69
Insecurity	1. You do not consider it safe giving out a credit card number over a computer. 2. The human touch is very important when doing business with a company.* 3. You do not consider it safe to do any kind of financial business online. 4. You do not feel confident doing business with a place that can only be reached online. 5. You worry that information you send over the internet will be seen by other people.	Five 7-point items anchored by "strongly disagree" [1] and "strongly agree" [7], adapted from Rojas-Mendez, Parasuraman, and Papadopoulos (2017).	α = 0.85
Perceived critical mass	1. Most people in my peer group frequently use Smart Devices. 2. Most people in my community frequently use Smart Devices. 3. My family/friends frequently use Smart Devices. 4. Most people I know use Smart Devices.	Four 7-point items anchored by "strongly disagree" [1] and "strongly agree" [7], adapted from Hsu and Lin (2016).	α = 0.95
Perceived compatibility	1. Using Smart Devices is compatible with all aspects of my daily life.* 2. I think that using Smart Devices fits well with the way I like to live. 3. Using Smart Devices fits into my lifestyle.	Three 7-point items anchored by "strongly disagree" [1] and "strongly agree" [7], adapted from Hsu and Lin (2016).	α = 0.95

Number and complementarity of smart devices	1. I think a good number of Smart Devices can be used. 2. I could easily find circumstances in which I can use Smart Devices. 3. A wide range of Smart Device products is available. 4. A wide range of apps concerning Smart Devices are available on smartphone.	Five 7-point items anchored by "strongly disagree" [1] and "strongly agree" [7], adapted from Hsu and Lin (2016).	α = 0.80

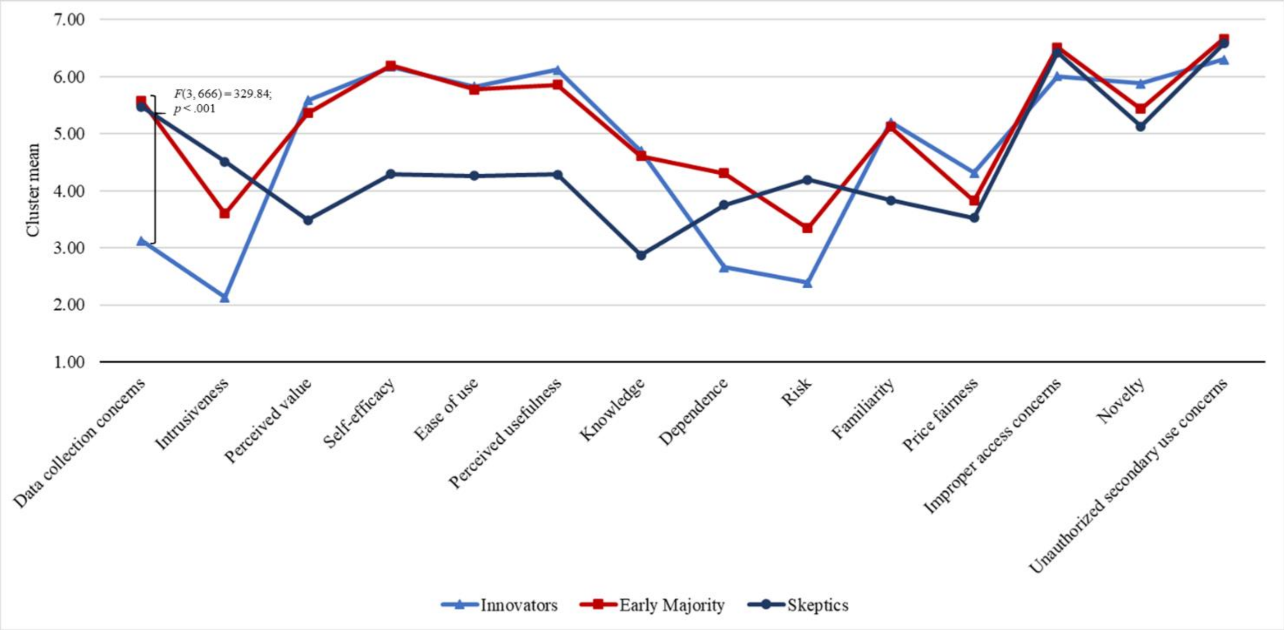
*Items delated after scale reliability test.

Table 3. Cluster Analysis Consumer Characteristics by Cluster.

		Cluster						Comparison tests
		Innovators		Early Majority		Skeptics		
		Cluster 1		Cluster 2		Cluster 3		
	Cluster size (%)	222 (33.18%)		269 (40.21%)		178 (26.61%)		
								F value (df); p
Clustering variables	Data collection concerns (DCC)	3.12 (1.29)	(2; 3)	5.58 (0.94)	(1)	5.48 (1.23)	(1)	329.84 (666); p < .001
	Unautho-rized secondary use concerns	6.30 (1.03)	(2; 3)	6.66 (0.62)	(1)	6.58 (0.77)	(1)	12.49 (666); p < .001
	Improper access concerns	6.01 (1.09)	(2; 3)	6.52 (0.65)	(1)	6.42 (0.81)	(1)	22.42 (666); p < .001
	Self-efficacy	6.17 (1.01)	(3)	6.20 (0.74)	(3)	4.29 (1.40)	(1; 2)	216.54 (666); p < .001
	Depen-dence	2.66 (1.14)	(2; 3)	4.31 (1.26)	(1; 3)	3.75 (1.44)	(1; 2)	103.55 (666); p < .001
	Intusive-ness	2.13 (0.75)	(2; 3)	3.60 (1.11)	(1; 3)	4.51 (1.37)	(1; 2)	250.13 (666); p < .001
	Novelty	5.89 (0.98)	(2; 3)	5.43 (1.18)	(1; 3)	5.13 (1.29)	(1; 2)	22.02 (666); p < .001
	Familia-rity	5.20 (1.33)	(3)	5.12 (1.41)	(3)	3.83 (1.23)	(1; 2)	64.27 (666); p < .001
	Know-ledge	4.70 (1.34)	(3)	4.61 (1.33)	(3)	2.87 (1.22)	(1; 2)	121.82 (666); p < .001
	Perceived usefulness	6.12 (0.77)	(2; 3)	5.86 (0.85)	(1; 3)	4.29 (1.31)	(1; 2)	201.91 (666); p < .001
	Perceived value	5.59 (0.93)	(3)	5.36 (0.95)	(3)	3.49 (1.29)	(1; 2)	235.38 (666); p < .001
	Price fairness	4.31 (1.00)	(2; 3)	3.83 (1.17)	(1; 3)	3.52 (1.03)	(1; 2)	27.49 (666); p < .001
	Risk	2.39 (1.22)	(2; 3)	3.35 (1.35)	(1; 3)	4.20 (1.28)	(1; 2)	98.87 (666); p < .001
	Ease of use	5.83 (0.84)	(3)	5.78 (0.72)	(3)	4.26 (1.05)	(1; 2)	211.94 (666); p < .001

Outcome variables	Purchase intention	5.94 (1.11)	(2; 3)	5.57 (1.33)	(1; 3)	3.70 (1.63)	(1; 2)	153.06 (666); p < .001
	Positive WOM	5.14 (1.33)	(2; 3)	4.71 (1.29)	(1; 3)	2.84 (1.40)	(1; 2)	162.82 (666); p < .001
Individual traits	Optimism	5.63 (0.96)	(3)	5.44 (0.95)	(3)	4.12 (1.24)	(1; 2)	120.73 (666); p < .001
	Innovati-veness	4.78 (1.39)	(3)	4.65 (1.37)	(3)	3.30 (1.27)	(1; 2)	71.63 (666); p < .001
	Discom-fort	3.43 (1.02)	(2; 3)	4.06 (0.96)	(1; 3)	4.43 (0.97)	(1; 2)	54.47 (666); p < .001
	Insecurity	2.73 (1.26)	(2; 3)	3.90 (1.40)	(1)	3.87 (1.42)	(1)	53.50 (666); p < .001
Network externalities	Perceived critical mass	5.64 (1.35)	(2; 3)	6.07 (1.03)	(1; 3)	4.28 (1.72)	(1; 2)	97.38 (666); p < .001
	Perceived compati-bility	5.72 (1.15)	(2; 3)	5.25 (1.18)	(1; 3)	3.22 (1.52)	(1; 2)	211.00 (666); p < .001
	Number and comple-mentarity of smart devices	6.21 (0.73)	(3)	6.10 (0.66)	(3)	4.84 (0.98)	(1; 2)	186.76 (666); p < .001
Number of smart devices owned		3.36 (1.38)	(2; 3)	2.95 (1.26)	(1; 3)	2.37 (1.33)	(1; 2)	27.70 (666); p < .001
Type of smart devices owned	Traditional (smartphone, tablet, laptop) %	25.68%		29.00%		43.26%		
	Non-traditional %	74.32%		71.00%		56.74%		
Demogra-phic information	Gender (% of women)	52.70%		52.42%		47.19%		
	Age (% < 46 years)	61.26%		68.40%		42.70%		

Figure 1. Factors Pro and Against the Adoption of AI-enabled Products



Findings

Cluster 1 includes Innovators, who show the highest purchase and WOM intentions. In relation to barriers to adopting AI-enabled products, they offer the lowest mean values for DCC, unauthorized secondary use concerns, improper access concerns, intrusiveness, dependence, and risk. This cluster indicates high levels of novelty, familiarity, perceived usefulness, perceived value, price fairness, ease of use, self-efficacy, and knowledge. Moreover, it scores lowest on the traits of discomfort and insecurity and high perceived network externalities of AI-enabled products.

Cluster 3 is composed of Skeptics. These consumers exhibit the lowest means for both purchase and WOM intentions. This segment is significantly more concerned about data collection, unauthorized secondary use, improper access, intrusiveness, dependence, and risk than the Innovators. Skeptics provide the lowest means for self-efficacy, novelty, familiarity, perceived usefulness, perceived value, price fairness, knowledge, and ease of use. Furthermore, compared with the other segments, Skeptics are significantly higher on discomfort traits and lower on innovativeness and optimism. Finally, this cluster shows the lowest means, significantly different from the other two clusters, on all the network externalities.

Cluster 2 is composed of the Early Majority, and it occupies an intermediate position, with intermediate values for both purchase and WOM intentions. It is significantly different from the other two clusters with regard to the barriers associated with intrusiveness, dependence, novelty, perceived usefulness, price fairness, and risk, as well as the discomfort trait. Early Majority consumers also are similar to Innovators when it comes to functional barriers (i.e., ease of use, familiarity, perceived value, and knowledge), the psychological self-efficacy barrier, positive individual traits (i.e., innovativeness and optimism), and the complementarity of network externalities. Yet they are similar to Skeptics when it comes to psychological barriers (i.e., DCC, unauthorized secondary use concerns, improper access concerns) and the negative insecurity trait.

The three segments differ in the relative importance they attribute to specific barriers to the adoption of AI-enabled products. In particular, Clusters 1 and 3 differ significantly in relation to all the barriers; Cluster 2 is similar to Cluster 1 across most functional barriers (i.e., perceived value, familiarity, knowledge, ease of use) and similar to Cluster 3 or intermediate between the two clusters for the psychological barriers. Moreover, DCC represents a significant barrier to AI-enabled product adoption for the Early Majority and Skeptics. Thus, the results confirm the presence of several barriers to consumers' adoption of AI-enabled products, depending on which consumers express a specific level of intention to adopt. Furthermore, DCC is the most important barrier in profiling consumers and assigning them to the three clusters.

General discussion

Even as we enter a new decade, one that was predicted to be the era of SOs, consumers remain reluctant to buy these products, due to several barriers that they experience when considering the purchase of a SO. The marketing literature about how consumers respond to innovations refers to two research paradigms (Laukkanen, 2016): the innovation adoption paradigm and the resistance to innovation paradigm. These two streams of literature have identified several factors that can respectively lead or inhibit consumers in the adoption of innovations and, consequently, in the adoption of SOs (e.g., Johnson et al., 2018; Laukkanen, 2016; Laukkanen et al., 2007; Mani & Chouk, 2017, 2018). However, two aspects must be considered. First, literature that considers consumers' reactions to innovations is fragmented in terms of both conceptual models and theories adopted and barriers identified and type of innovations. Second, SOs are a specific type of innovation, due to their specific technical features and characteristics (i.e., agency, autonomy, and authority) (Hoffman & Novak, 2018; Novak & Hoffman, 2019). This second aspect suggests that the reasons leading consumers to avoid the adoption of SOs could be different from the reasons underlying the non-adoption of a general innovation. Therefore, investigating what are the specific factors that lead to or inhibit the adoption of SOs is of pivotal importance. With two online studies we identified the barriers to consumer adoption of SOs (Study 1) and we identified the most important barrier in hindering consumers' adoption of these products (Study 2). The results of Study 1 and Study 2 provide relevant insights into consumer perceptions about the barriers of SO adoption. Price and value have emerged in Study 1 as major obstacles. These findings are partially supported in Study 2. However, Study 2 revealed that data collection concerns is the most important barrier in profiling consumers and assigning them to the three different clusters.

Theoretical implications

This research contributes to the existing literature in two ways. First, we systematize the literature about consumer adoption and resistance to SOs by. Starting from the literature about innovation adoption and resistance, and then moving to the one about SOs adoption and resistance, we put together different factors that can play a role in leading or hindering consumers in adopting a SO. Second, we identify new barriers to the adoption of SOs (i.e., risky purchase and privacy concerns). Finally, we identify the most important barrier to consumers' adoption of SOs and provided a detailed profile of different types of consumers in term of psychological barriers, functional barriers, network externalities, and individual traits.

Managerial implications

For companies and managers seeking to boost the mainstream diffusion of SOs, our study provides useful insights into the factors that can lead or hinder consumers' adoption of SOs. Study 1 shows that in the SO context there are some new barriers that were missing in the previous innovation domain (i.e., risky purchase and privacy concerns). Managers need to account for these new barriers if they want to increase the SO adoption. Study 2 highlights the role of data collection concerns as the main barrier to consumers' adoption of SOs. Managers should pay attention to this barrier and implement some marketing strategies that aim at reducing consumers' data collection concerns (e.g., implementing a communication strategy aiming at reassuring the consumer about the firm's privacy policy or adopting a privacy by design approach when designing products or services).

Limitations and further research

Some limitations of this study provide avenues for continued research. First, we asked respondents to report their barriers to the adoption of SOs in general without focusing on a specific type of SO. The different technical features of different types of SO can play a role in activating certain barriers compared to others. Focusing on a specific type of SO (e.g., a smartwatch or a smart speaker) can help researchers to identify specific barriers related to that specific SO. Second, we did not ask for brand-related variable (e.g., brand attitude, brand familiarity, brand trust, and brand loyalty). We decided to not ask for those variables in order to avoid some confounding effects played by the brand and so to make the role of the brand less salient during the recall task and the quantitative survey. However, consumers may express varying levels of barriers, depending on their relationships with a brand. Further research should investigate the role played by the brand in shaping the barriers to the adoption of SOs.

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Details Matter! Whether, How, and When Information about Algorithms' Functioning Reduces Data Collection Concerns in the Artificial Intelligence Era

Introduction

In the past decade, market forecasts (ABI Research, 2014; Cisco, 2014; Ericsson, 2010) and consulting reports (Gartner, 2018; Manyika et al., 2015) predicted that 2020 would be a breakthrough year for artificial intelligence (AI). Euphoric projections foresaw mainstream adoption of AI-enabled products (e.g., autonomous vehicles, smart robots, virtual assistants, conversational platforms) and connections of an estimated 50 billion devices to the Internet. But the reality of 2020 has not lived up to these predictions; not only have AI-enabled products not spread to the mainstream (Newman, 2020), but only 20 billion connected devices are actually in use (Kranz, 2019), suggesting that "the road to mass adoption of the smart home will likely be a long and bumpy one" (Morrissey, 2019).

Why do consumers remain reluctant to buy AI-enabled products? The key factors seemingly relate to both technological features (e.g., use complexity, value offered, risk, object intrusiveness; Hubert et al., 2019; Johnson, Kiser, Washington, and Torres, 2018; Laukkanen, 2016; Lee and Coughlin, 2015; Mani and Chouk, 2017, 2018; Ram and Sheth, 1989) and consumers' individual characteristics (e.g., data collection concerns, desire to avoid becoming dependent on AI-enabled products, low usage self-efficacy; Hsu and Lin, 2016; Johnson et al., 2018; Lee and Coughlin, 2015; Mani and Chouk, 2017, 2018; Ram and Sheth, 1989). Notably, data collection concerns (DCC), defined as consumers' concerns about how companies gather and use their personal data (Malhotra, Kim, and Agarwal, 2004; Smith, Milberg, and Burke, 1996) appear strongly influential, such that AI technologies' ability to collect and process huge amounts of highly personal data prompt consumers to avoid or delay their adoption of AI-enabled products (Berger-de Leon, Reinbacher, and Wee, 2018; Insider Intelligence, 2020). According to a recent survey, 87% of sales delays stem from consumers' privacy concerns (Cisco, 2019). That is, DCC appears to hinder purchase intentions, being a crucial concern for consumers. As a consequence, mainstream diffusion of AI-enabled products will require reductions in DCC, or else business efforts to neutralize or mitigate DCC's adverse effects.

Some studies suggest that granting consumers control over their personal data management (i.e., *control*) is key to inhibiting DCC (e.g., Malhotra, Kim, and Agarwal, 2004; Xu, Teo, Tan, and Agarwal, 2012), and some companies (e.g., Apple, Facebook) have implemented policies to help consumers see which information is being collected and decide whether to allow such collections or when to remove their information from a company's database. Beyond this direct effect of control on DCC, it also seems likely to interact with other relevant inhibitors, though these combined effects surprisingly have not been much studied (Aguirre, Mahr, Grewal, Ruyter, and Wetzels, 2015; Martin, Borah, and Palmatier, 2017; Martin and Murphy, 2017). For example, the quality of information that companies provide to explain how their AI-enabled products' algorithms process personal data to produce a certain outcome, or *information detail*, is critical in AI contexts (Mastercard, 2020; Puntoni, Reczek, Giesler, and Botti, forthcoming; Rai, 2020), because consumers generally lack sophisticated knowledge about how the algorithms work, which strongly feeds their DCC (Cisco, 2019). Providing consumers with detailed information about the functioning of AI-enabled products' algorithms should decrease DCC, alone and in interaction with control. Therefore, we investigate whether, by which pathways, and in which settings the provision of detailed information combines with control to reduce DCC in an AI-enabled product domain.

In turn, we contribute to literature on consumers' privacy concerns and DCC in three main ways (Malhotra, Kim, and Agarwal, 2004; Smith, Milberg, and Burke, 1996). First, we conceptually propose and empirically test a novel combination of DCC inhibitors (Martin, Borah, and Palmatier, 2017; Martin and Murphy, 2017) and thereby determine that providing consumers with a combination of detailed information and high control leads to the lowest level of DCC (Studies 1 and 2). Second, we specify the psychological processes underlying these observed effects. We propose a new, previously untested psychological mechanism, reflecting serial mediation by communication effectiveness (Sharma and Patterson, 1999) and interpretive inferences (Alba and Hutchinson, 1987).

The effect of detailed information provision on DCC is mediated by the perceived effectiveness of that detailed information in terms of explaining the algorithm's functioning, which then leads consumers to understand the utility of providing their personal data. Third, we identify relevant, previously untested boundary conditions for the hypothesized effects; specifically, the relationship between information detail and DCC arises only in the presence of certain benefits. For this contribution, we leverage research into consumers' motivation to buy and use brands (Park, Jaworski, and MacInnis, 1986; Park, MacInnis, and Priester, 2006) and AI-enabled products (Choi and Kim, 2016; McLean and Osei-Frimpong, 2019; Rauschnabel, He, and Ro, 2018), which predicts the impacts of different types of benefits, such as utilitarian, symbolic, or hedonic. We demonstrate, for the first time, that utilitarian benefits (i.e., benefits related to efficiency and helpfulness) and symbolic benefits (i.e., benefits related to prestige and status signaling) enhance the effect of information detail on DCC, but hedonic benefits (i.e., benefits related to enjoyment and fun) nullify it.

With these findings, our research also offers relevant practical implications for promoting the diffusion of AI-enabled products. Companies can build on our results to design effective communication strategies that reduce DCC. In particular, they should provide consumers with detailed information about how their AI-enabled products' algorithms process their data to produce the best outcomes meeting individual needs (i.e., highly personalized product offerings, recommendations, services, and communications). They also can encourage consumers' confidence by granting them more control over their personal data management. Finally, we recommend that companies take great care in framing their communication about the benefits that consumers can gain from using AI-enabled products.

Conceptual Foundations and Hypotheses

DCC and Control

Scholarly attention to DCC has escalated in various marketing contexts, including retailing (Inman and Nikolova, 2017), targeted and location-based advertising, recommendation systems, personalization (Martin and Murphy, 2017), consumers' trust in websites and e-commerce (Martin, 2018), product design strategies (Luchs, Swan, and Creusen, 2016), and online relationship marketing (Steinhoff, Arli, Weaven, and Kozlenkova, 2019). This increased attention is not surprising. The undesired effects of widespread access to consumers' personal data are pervasive in people's everyday life, creating vulnerability to data breaches, privacy invasions, and intrusive marketing communications (Martin and Murphy, 2017; Puntoni et al., forthcoming). The tremendous amount of data required by any AI-driven ecosystem, for its development and functioning, also places DCC at the center of AI discussions (Davenport, Guha, Grewal, and Bressgott, 2019; Rai, 2020; Thomaz, Salge, Karahanna, and Hulland, 2020; Tucker, 2018).

Yet AI should not be solely a source of concern, because by analyzing users' personal data it offers undeniable benefits to them. It allows for highly personalized product offerings, recommendations, services, and communications that better meet individual needs (Chandy, Hassan, and Mukherji, 2017; Martin and Murphy, 2017; Puntoni et al., forthcoming; Verganti, Vendraminelli, and Iansiti, 2020). The partnership between Trivago and Tripl offers a good example, in that users obtain highly personalized travel suggestions (Koksal, 2020). Cosmetic companies such as IL MAKIAGE and Prose collect vast amounts of user data, apply algorithms to analyze them, and then offer users incredibly customized products (Moore, 2019). Despite these benefits though, consumers seem reluctant to disclose their personal information, mainly because they worry about how companies collect and manage their data.

Marketing literature accordingly acknowledges the complicated role of privacy, and DCC more specifically, for consumers and its influences on their behaviors (Martin and Murphy, 2017). In particular, DCC can reduce purchase intentions (Goldfarb and Tucker, 2011a, 2011b), click-through rates on targeted ads (Aguirre et al., 2015; Tucker, 2014), advertising effectiveness (Kim, Barasz, and

John, 2019), and uses of smart objects (Novak and Hoffman, 2019). Growing research has attempted to identify business factors (e.g., marketing strategies) to neutralize these adverse effects of DCC (Aguirre et al., 2015; Martin, Borah, and Palmatier, 2017), and Martin and Murphy (2017) specify three main inhibitors: trust, personalization, and control. In particular, control, defined as consumers' "ability to determine what information they give to the firm, [*and*] how it is used" (Martin, Borah, and Palmatier, 2017, p. 43), is seemingly the most important element. Firms giving consumers control represents a signal of the firms' good intentions with regard to managing consumers' personal data (Malhotra, Kim, and Agarwal, 2004). This central influence of control also emerges in empirical studies in Internet and digital service contexts. For example, Facebook users exhibit higher click-through rates on personalized advertising when they have more control over privacy settings (Tucker, 2014). Higher levels of control also mitigate the effect of customers' sense of vulnerability on their behaviors (Martin, Borah, and Palmatier, 2017). We adopt Martin, Borah, and Palmatier's (2017) definition of control and operationalize it for our AI study setting by creating a notification that tells consumers they can manage and decide which information they want to provide to an AI-enabled product and which information they want to delete. We posit that providing consumers with more control will significantly reduce their DCC. Moving beyond this widely acknowledged role of control as a default, "must have" condition to mitigate DCC (Malhotra, Kim, and Agarwal, 2004; Xu et al., 2012), we also consider its combined effect with other relevant inhibitors, a topic that has been much less investigated (Martin, Borah, and Palmatier, 2017; Aguirre et al., 2015). We argue that control might magnify the effect of information detail, as a novel, thus far under-researched DCC inhibitor. As we noted previously, information detail refers to the level of information that companies provide to explain how AI-enabled products' algorithms process personal data to produce a certain outcome.

The Combined Effect of Control and Information Detail on DCC

Across various empirical contexts, people react positively to explanations of the modalities and implications of their actions. In a marketing context, this placebo effect emerges in studies that show that strong advertising claims about a drink's ability to improve mental functioning enhance participants' cognitive task performance (Shiv, Carmon, and Ariely, 2005). When consumers receive information about why they have received a specific, online, personalized advertisement, both click-through rates and the level of ad effectiveness increase (Aguirre et al., 2015; Kim, Barasz, and John, 2019). That is, making people aware of some aspects of a topic or an action, which is a basis of the placebo effect, represents an educational process, in the sense that providing detailed information can be a way to educate people about that topic. A detailed information format explicitly enables companies to provide customers with more complete explanations about product attributes, which implies better quality information too (Keller and Staelin, 1987; MacKenzie, 1986). Higher quality of the information then increases the effectiveness of the decision that a person makes, on the basis of the information received (Keller and Staelin, 1987).

In the AI domain, scholars have started to investigate whether educating consumers about an algorithm's functioning might influence their attitudes and behaviors (Puntoni et al., forthcoming; Rai, 2020). Such educational efforts would clarify how the outcomes that an algorithm produces (e.g., highly personalized product offerings, recommendations, services, and communications) result from a decision-making process that relies on consumers' data. Providing users with effective explanations of this decision-making process also may influence their actions in response to the outcome provided by that algorithm (e.g., accept or reject the recommendations) (André et al., 2018). In computer–human interaction research, some early evidence has affirmed that explaining how the algorithm processes data to produce an outcome can increase a user's objective understanding of its inner workings (Cheng et al., 2019).

Along these lines, we propose that a placebo effect applies in the AI realm, such that providing consumers with detailed information (vs. no information as a baseline) about how AI-enabled products' algorithms work, in combination with a high level of control, generates lower DCC. We operationalize information detail by the level of concreteness and vividness of the information that companies provide (MacKenzie, 1986; Gleim, Smith, Andrews, and Cronin, 2013). Formally, we predict:

H1: When consumers receive high (vs. low) control, detailed information (vs. no information) decreases DCC.

Beyond the two extremes (i.e., no information vs. detailed information), companies might offer information with a lower level of detail (e.g., simple information with minimal concreteness and vividness). In Gleim et al.'s (2013) comparison of the effects of different levels of information detail (no, simple, and detailed information) on consumers' purchase intentions, quality beliefs, and value beliefs about green products, they find that the effects differ across the dependent variables, such that the detailed information does not always result in the strongest effect. Without detailed insights into how varying levels of information detail might produce mixed effects on consumers' reactions, we assess the effect of these different levels on DCC, when consumers consistently have high levels of control.

Detailed Information Facilitates Understanding of the Utility of Providing Personal Data

Information detail arguably should reduce DCC through perceived communication effectiveness, which produces inferences about the utility of providing personal data to AI-enabled products. That is, AI algorithms are embedded in people's everyday lives, such that people rely on them when they shop online, choose movies on Netflix, leave for work earlier to achieve a shorter commute according to AI-powered predictions, listen to music on Spotify, use social networks, develop workout plans, or schedule meetings. Nevertheless, consumers remain unfamiliar about and wary of AI algorithms, which feature substantial complexity (Puntoni et al., forthcoming; Rai, 2020). Understanding how AI algorithms work is a challenging task for people who are not computing experts, and this widespread "literacy gap" makes it difficult for consumers to understand why AI algorithms need so much personal information or what they do with the information they provide

(Cheng et al., 2019; Rai, 2020). Developing literacy and understanding about AI algorithms should enhance consumers' awareness of the utility of providing personal data though.

The notion of literacy is not exclusive to AI; assessments of complex services, such as legal, medical, or financial counseling, involve analogous challenges that stem from customers' lack of domain-specific know-how (Sharma and Patterson, 1999). More education helps them make quality judgments and lower their risk perceptions in such service settings. In these cases, education often relies on effective communication with customers, such that full information gets delivered to the clients at the right time, in an empathetic manner, and using language that the clients can understand (Sharma and Patterson, 1999). Similarly, for AI-enabled product domains, literacy about AI algorithms can improve if consumers receive detailed information about the algorithms and their functions. The level of detail represents a communication modality, such that more detail should lead consumers to regard the communication as clearer, more understandable, and more effective. In turn, more effective communication enables consumers to understand the utility of providing personal data (André et al., 2018). That is, detailed information about AI algorithms and their functions operates as a signal of good communication effectiveness, which leads consumers to make positive inferences about the utility of providing their personal data.

Understanding the Utility of Providing Personal Data and DCC

Although consumers possess different levels of knowledge about AI-enabled products and their algorithms, they generally should be aware of two elements. First, they know that AI-enabled products use their data, because they consent to the gathering of their personal information. Second, they can assess the outcome they receive from AI-enabled products, in terms of its personalization and accuracy in matching their needs. With these two pieces of information, consumers likely deduce that the quality of the outcome depends on the data processing by AI algorithms. Such interpretive inferences (Alba and Hutchinson, 1987), if correct, coincide with the intended meaning. However, inaccurate inferences are possible, and the ability to achieve good inferences depends on the knowledge that people have about the focal topic (Alba and Hutchinson, 1987).

Applying the notion of interpretive inferences to an AI context, we argue that people who are more knowledgeable about how AI algorithms work have less difficulty making correct interpretive inferences, compared with those who are less knowledgeable. Therefore, effective communication about AI algorithms should be critical for helping consumers achieve accurate interpretative inferences. That is, when people receive detailed information about AI algorithm functions, they perceive higher levels of communication effectiveness and gain more understanding of the utility of providing personal data. As marketing literature has shown, consumers' product inferences affect their attitudes, judgments, and choices (Fishbein and Ajzen, 1975; Huber and Mccann, 1982; Lynch and Srull, 1982; Olson, 1978). Therefore, increased understanding of the utility of providing personal data should have a negative effect on DCC, through a two-step mediation process: Detailed information increases the perceived effectiveness of the communication, which increases understanding of the utility of providing personal data, which then reduces DCC.

H2: The reduction in DCC, in response to detailed information, is mediated by perceived communication effectiveness, which increases understanding of the utility of providing personal data.

Utilitarian, Symbolic, and Hedonic Benefits

In this section, we consider the type of benefits that consumers might anticipate, in return for providing data, as a potential boundary condition of the relationship between information detail and DCC. We propose that information detail reduces DCC if these benefits are utilitarian or symbolic, but if the benefits are hedonic, the effect of information detail on DCC may be attenuated. Consistent with well-established consumer behavior literature (Park, Jaworski, and MacInnis, 1986; Park, MacInnis, and Priester, 2006), the use of AI-enabled products should provide three main types of benefits (Choi and Kim, 2016; McLean and Osei-Frimpong, 2019; Rauschnabel, He, and Ro, 2018):

utilitarian, symbolic, and hedonic. Utilitarian benefits refer to efficient, useful, and convenient aspects of consumer activities (Choi and Kim, 2016; McLean and Osei-Frimpong, 2019; Rauschnabel, He, and Ro, 2018). Symbolic benefits arise because people believe they can improve their status or social identity by using SO (Choi and Kim, 2016; McLean and Osei-Frimpong, 2019; Rauschnabel, He, and Ro, 2018). Hedonic benefits reflect an individual emotional sphere, featuring the enjoyable, pleasant aspects that an interaction with AI-enabled products involves (Choi and Kim, 2016; McLean and Osei-Frimpong, 2019; Rauschnabel, He, and Ro, 2018).

Hedonic products, compared with symbolic and functional ones, offer interesting peculiarities. They can alter consumers' attention, moving it away from negative stimuli and toward positive emotions related to pleasure. Pleasure-related emotions in turn can affect other feelings and behaviors, such as by eliciting a sense of relaxation or encouraging self-indulgence (Park, MacInnis, and Priester, 2006). An investigation of personal data sharing behaviors in the context of viral promotional advergames shows that perceived playfulness leads participants to become totally absorbed in the action, which then increases their tendency to disclose their personal information, because the emotional stimuli distract consumers and lead them to forget they are being subjected to persuasion efforts (Zhao and Renard, 2018).

Similarly, we operationalize the benefits that consumers might derive from using AI-enabled products as utilitarian (i.e., efficient and helpful), symbolic (i.e., prestigious and signals of status), or hedonic (i.e., enjoyable and funny) (Etkin, 2016). We predict that the type of benefit moderates the effect of information detail on DCC, such that the implications of hedonic benefits (e.g., moving negative thoughts to the background, allowing consumers to focus on the pleasure of using AI-enabled products) reduce their concerns about the collection of personal data required by AI-enabled products. Thus, consumers who receive hedonic benefits do not need detailed information about AI algorithms to the same extent; the effect of detailed information on DCC, relative to that of less detailed information, should be attenuated for these consumers.

H3: The reduction in DCC, in response to detailed information, is moderated by the type of benefits, such that for utilitarian or symbolic benefits, the effect of detailed information on DCC is negative, but for hedonic benefits, the effect of detailed information on DCC is attenuated.

In summary, in conditions marked by high control, consumers who receive detailed information should express lower levels of DCC than those provided with less detailed or no information. We anticipate that this effect is fully mediated by the perceived effectiveness of detailed information as a communication format, such that it helps consumers understand the utility of providing personal data, which then decreases their DCC. The type of benefits consumers obtain from using AI-enabled products also offers a potentially relevant boundary condition. When consumers use AI-enabled products to achieve utilitarian and symbolic benefits, detailed information may be an effective instrument to reduce DCC, but detailed information likely has insignificant effects if consumers receive hedonic benefits in exchange for their personal data.

Overview of Studies

We test the hypotheses with four online, experimental studies. Table 1 provides an overview of the empirical approach; Figure 1 depicts the conceptual model tested in each study. With Study 1, we test whether, for consumers with a high level of control, detailed information (vs. no information) reduces DCC (Figure 1, Panel A); then as a further test of H1, in Study 2 we assess whether detailed information prompts a greater decrease in DCC compared with no or less detailed information (Figure 1, Panel B). Study 3 investigates the psychological mechanisms of this information detail effect and tests H2, regarding whether information detail reduces DCC through the serial mediation of perceived communication effectiveness and understanding the utility of providing personal data (Figure 1, Panel C). Finally, Study 4 tests H3 by considering different benefits consumers can get from using AI-enabled products, as a moderating factor that might facilitate (utilitarian or symbolic) or suppress (hedonic) the effects of information detail on DCC (Figure 1, Panel D).

All the studies use fitness trackers as the focal product category. These tools generate hyperpersonalized fitness profiles and plans, in exchange for extensive collection and aggregation of users' personal data (Uzzi, 2019). To enhance the generalizability of our findings though, we alternate the kinds of fitness trackers across studies, including a smart watch in Studies 1–3 and a smart band in Study 4. Both formats share some features in common (e.g., worn on the wrist, tell time, offer health/fitness features) but differ in the variety of functionalities they offer (e.g., smart bands are fitness-focused, smart watches encompass diverse fitness tracking, communication, and phone functionalities; Johnson, 2020) (for further details about the products and their focal features, see Appendix A). To avoid any confounding effects of brand familiarity or brand awareness, all studies use fictitious brand names: Top-Fit (watch) and FitBand (band).

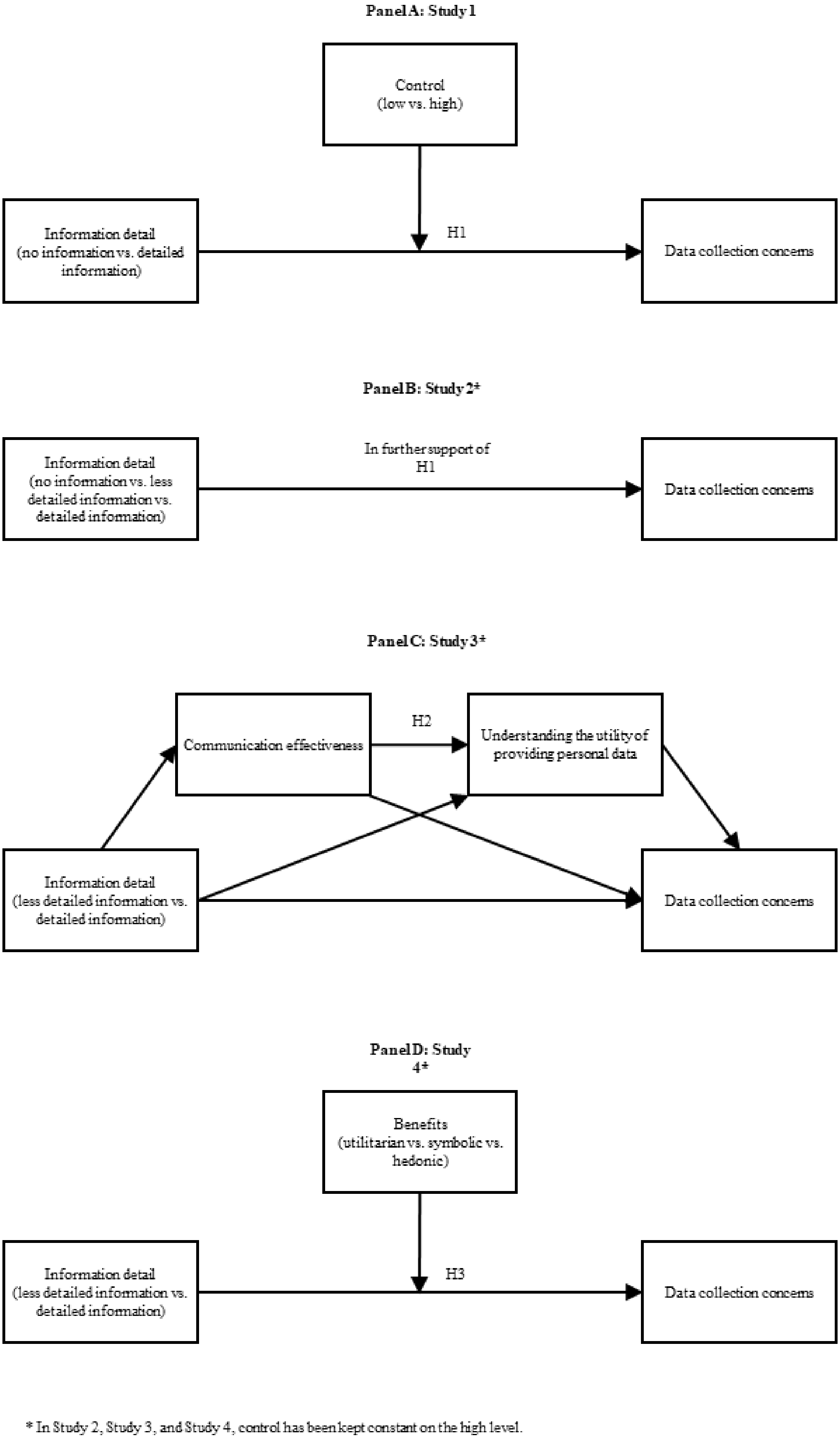
In all studies, we control for consumers' socio-demographic characteristics (age, gender, and education) and familiarity with smart devices. These variables tend to influence privacy concerns (e.g., Malhotra, Kim, and Agarwal, 2004; Martin, Borah, and Palmatier, 2017) and people's ability to make correct inferences about objects (e.g., Alba and Hutchinson, 1987; MacKenzie 1986), so they potentially have an impact on DCC also.

Table 1. Overview of the Empirical Research

Aim of each study	Variables analyzed	Empirical context	Hypotheses tested
Study 1 examines the *moderating* effect of control on the relationship between information detail and DCC.	X: Manipulated information detail Y: DCC W: Manipulated level of control	SO: Top-Fit, a smart watch provided with several advanced functionalities among which the equipment to provide personalized nutrition recommendations and healthy meal plans. Stimuli: description of Top-Fit, description of what data the algorithm needs, quality of the nutritional plan recommended, information about how the algorithm works, and consumers' level of control over their personal data. No information vs. detailed information. Low vs. high level of control.	**H1**

		Research design: between-subjects experiment. N= 360.	
Study 2 examines the effect of different levels of information detail on DCC. The high level of control is kept constant.	X: Manipulated information detail Y: DCC	SO: as in Study 1. Stimuli: as in Study 1. No information vs. less detailed information vs. detailed information. High level of control. Research design: between-subjects experiment. N= 212.	In further support of **H1**
Study 3 examines the serial *mediating* role of communication effectiveness and understanding the utility of providing personal data in reducing DCC. The high level of control is kept constant.	X: Manipulated information detail Ms: Communication effectiveness and understanding the utility of providing personal data Y: DCC	SO: as in previous studies. Stimuli: as in previous studies. Less detailed information vs. detailed information. High level of control. Research design: between-subjects experiment. N= 178.	**H2**
Study 4 examines the *moderating* effect of type of benefits on the relationship between information detail and DCC. The high level of control is kept constant.	X: Manipulated information detail Y: DCC W: Manipulated type of benefits	SO: FitBand, a smart band provided with few basic functionalities and an advanced equipment to provide personalized nutrition recommendations and healthy meal plans. Stimuli: description of FitBand, description of what type of benefits consumers gain from using of the smart band, what data the algorithm needs, quality of the nutritional plan recommended, information about how the algorithm works, and consumers' level of control over their personal data. Less detailed information vs. detailed information. Utilitarian vs. symbolic vs. hedonic benefits. High level of control. Research design: between-subjects experiment. N= 433.	**H3**

Figure 1. The Conceptual Model.



Study 1: The Effect of Information Detail and Control on DCC

In Study 1, we predict that when consumers have high (low) control over their personal data, being exposed to detailed information does (not) decrease DCC, compared with a situation in which no information is provided (Table 1; Figure 1, Panel A).

Method

Participants and study design. We recruited 360 participants (47.2% men; M_{age} = 34.22 years, *SD* = 13.33; 46.7% high school, 39.7% bachelor's degree, 11.9% master's degree, 1.4% PhD, 0.3% lower than high school) from Prolific to take part in a 10-minute study in exchange for money. Participants were randomly assigned to a 2 (information detail: no vs. detailed information) × 2 (control: low vs. high) between-subjects design.

Procedure. All respondents read a passage introducing Top-Fit, a newly released smart watch with advanced fitness features that provide users with personalized nutrition recommendations. Respondents then had to engage in an imagination task, picturing themselves inside a consumer electronics store, staring at Top-Fit and reading its fitness app instructions. These instructions listed all the personal data that Top-Fit needs to generate personalized nutrition programs, so we manipulated both the level of information detail (no vs. detailed information) provided regarding how Top-Fit's algorithm processes users' data and the level of control (low vs. high). Respondents were randomly assigned to one of the four conditions. The stimuli, presented in Appendix A, had been pretested among a sample of 200 consumers and, as expected, differed significantly in the information detail and perceived control (for more details, see Appendix B, Panel A) they provided. After reading the scenario, participants in each condition provided their DCC, familiarity with smart devices, manipulation checks for perceived information detail, and perceived control (see Appendix C). Finally, they provided demographic information.

Results

Manipulation checks. The manipulations of information detail and control were successful. Respondents in the detailed information condition perceived the level of information as more detailed, compared with those in the no information condition. Also, respondents in the high control condition perceived higher levels of control, compared with those in the low control condition (see Appendix B, Panel A, for means and standard deviations; information detail $t(358) = -6.76$, $p < .001$; control $t(358) = -9.62$, $p < .001$).

DCC. We validated our predictions using a between-subjects analysis of covariance (ANCOVA) with DCC as the dependent variable and control (0 = low; 1 = high) as a moderator of the effect of information detail (0 = no information; 1 = detailed information) on DCC. As Table 2, Panel A, shows, we find a significant main effect of information detail on DCC, such that the mean DCC level reported by respondents in the detailed information condition ($M_{detailedinfo} = 5.16$, $SD = 1.71$) is significantly lower than that reported by respondents in the no information condition ($M_{noinfo} = 5.54$, $SD = 1.57$; $F(1, 352) = 4.84$, $p = .028$, $\eta^2 = .014$). The results indicate a significant main effect of control on DCC too. The mean DCC level reported by respondents in the high control condition ($M_{highcontrol} = 4.82$, $SD = 1.89$) is significantly lower than the mean DCC level reported in the low control condition ($M_{lowcontrol} = 5.87$, $SD = 1.16$; $F(1, 352) = 42.10$, $p < .001$, $\eta^2 = .107$). Next, in Table 2, Panel A, and Figure 2, we find a significant information detail × control interaction ($F(1, 352) = 6.36$, $p = .012$, $\eta^2 = .018$). According to a planned contrasts analysis, detailed information in the high control condition decreases DCC ($M_{noinfo} = 5.20$, $SD = 1.86$; $M_{detailedinfo} = 4.39$, $SD = 1.85$; $F(1, 352) = 10.77$, $p = .001$, $\eta^2 = .030$), whereas in the low control condition, we find no changes on DCC level due to the information detail ($M_{noinfo} = 5.85$, $SD = 1.14$; $M_{detailedinfo} = 5.88$, $SD = 1.19$; $F(1, 352) = .047$, $p = .828$, $\eta^2 = .000$) (see Table 2, Panel B).

The findings thus support H1: High consumer control magnifies the effect of detailed information for decreasing DCC. When consumers have detailed information about how AI algorithms process their personal data, their DCC diminishes, as long as they have been granted high levels of control. The effect vanishes at low levels of control.

Table 2. Moderating Effect of Control on the Relationship Between Information Detail and DCC

Panel A. Tests of Between-Subjects Effects

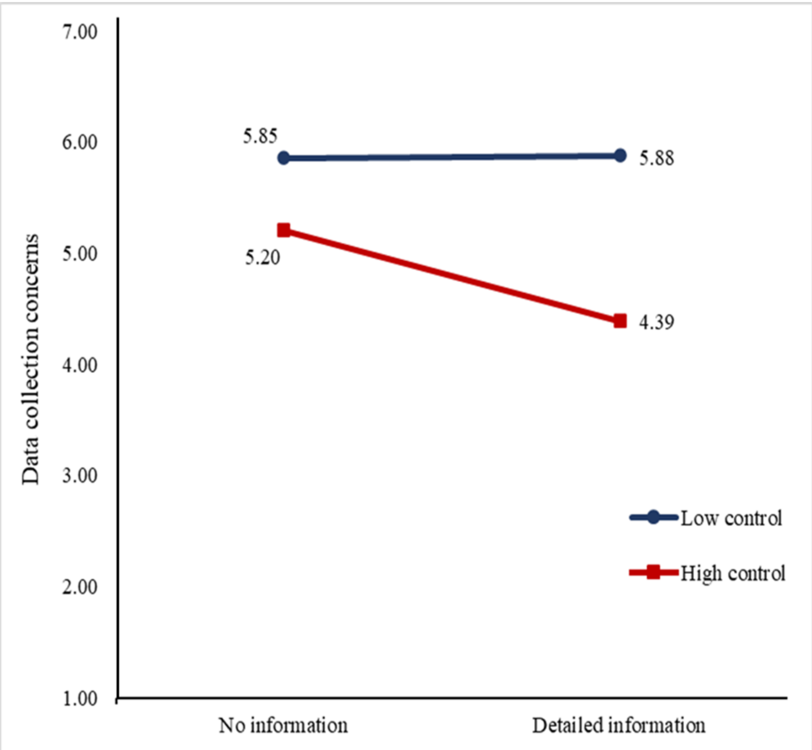
Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Intercept	199.930	1	199.930	84.581	< .001	.194
Gender	1.884	1	1.884	.797	.373	.002
Age	.154	1	.154	.065	.799	.000
Education	2.856	1	2.856	1.208	.272	.003
Familiarity with smart devices	3.327	1	3.327	1.407	.236	.004
Information detail	11.444	1	11.444	4.841	.028	.014
Control	99.509	1	99.509	42.097	< .001	.107
Information detail x Control	15.022	1	15.022	6.355	.012	.018
Error	832.051	352	2.364			

Panel B. Planned Contrasts Analysis Univariate Tests

Control		Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Low	Contrast	.111	1	.111	.047	.828	.000
	Error	832.051	352	2.364			
High	Contrast	25.457	1	25.457	10.769	.001	.030
	Error	832.051	352	2.364			

Each F tests the simple effects of Information detail within each level combination of the other effects shown. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.

Figure 2. Moderating Effect of Control on the Relationship Between Information Detail and DCC



Study 2: The Effect of Different Types of Information Detail on DCC

The manipulation of information detail in Study 1 (no vs. detailed information) cannot account fully for the effect of varying levels of information detail on DCC. Therefore, with Study 2 we test the effect of different levels of information detail (less detailed vs. detailed information) on DCC relative to a baseline, no information condition. We keep the level of consumers' control constant and high (Table 1; Figure 1, Panel B).

Method

Participants and study design. We recruited 212 participants (50.9% men; M_{age} = 34.76 years, *SD* = 12.80; 45.3% high school, 37.7% bachelor's degree, 13.7% master's degree, 2.4% PhD, 0.9% lower than high school) from Prolific to take part in a 10-minute study in exchange for money. Participants were randomly assigned to three information detail conditions (information detail: no vs. less detailed vs. detailed).

Procedure. All participants read the description about Top-Fit, engaged in an imagination task, and received the instructions from Study 1. We manipulated information detail at three levels and kept the level of control constant. The stimuli, as detailed in Appendix A, had been successfully pretested with a sample of 128 consumers, who confirmed that the levels differed significantly in their information detail. Consistent with our research design (i.e., control kept constant and high), the level of control was perceived as significantly higher than the scale midpoint (for more details, see Appendix B, Panel B). After reading the scenario, participants in each condition responded to the measures from Study 1: DCC, familiarity with smart devices, manipulation checks for perceived information detail, and perceived control (Appendix C), as well as demographic information.

Results

Manipulation check. The information detail manipulation was successful. Respondents in the detailed information condition perceived the level of information to be more detailed, compared with those in the no information and less detailed information conditions (see Appendix B, Panel B, for means and standard deviations; information detail $F(2, 209) = 18.40$, $p < .001$). The level of control also was correctly perceived as high (> scale midpoint of 4) ($t(211) = 5.22$, $p < .001$).

DCC. To assess the effect of different levels of information detail on DCC, we used a one-way ANCOVA for the between-subjects design with three levels. As Table 3, Panel A, shows, information detail (0 = no information; 1 = less detailed information; 2 = detailed information) has a significant effect on DCC ($F(2, 205) = 21.56$, $p < .001$, $\eta^2 = .174$). The planned contrast analysis confirms that the level of DCC is significantly different and lower as the level of information detail increases. Indeed, detailed information decreases DCC ($M_{detailedinfo} = 3.82$; $SD = 1.57$) compared to both less detailed information ($M_{lessdetailedinfo} = 4.65$; $SD = 1.59$) and no information ($M_{noinfo} = 5.53$; $SD = 1.13$; $t(209) = -5.98$, $p < .001$); more importantly, detailed information decreases DCC also in comparison with less detailed information only ($t(209) = -3.42$, $p = .001$) and, in turn, less detailed information decreases DCC compared to no information only ($t(209) = -3.61$, $p < .001$) (see Table 3, Panel B). The results of Study 2 thus provide further support for H1 and show that, assuming a high level of control, detailed information reduces DCC more than either the baseline no information condition or an information condition that simply provides less detail.

Table 3. Effect of Information Detail on DCC

Panel A. Tests of Between-Subjects Effects						
Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Intercept	158.974	1	158.974	75.874	< .001	.270
Gender	1.954	1	1.954	.932	.335	.005
Age	.009	1	.009	.004	.948	.000
Education	.139	1	.139	.066	.797	.000
Familiarity with smart devices	8.574	1	8.574	4.091	.044	.020
Information detail	90.397	2	45.199	21.564	< .001	.174
Error	429.678	205	2.096			

Panel B. Planned Contrasts Analysis					
Contrast	Value of Contrast	Std. Error	t	df	Sig.

Detailed information vs. Less detailed information and No information	-2.54	.42	-5.984	209	< .001
Detailed information vs. Less detailed information	-.83	.24	-3.416	209	.001
Less detailed information vs. No information	-.88	.24	-3.605	209	< .001

Study 3: Serial Mediation of Communication Effectiveness and Understanding the Utility of Providing Personal Data

With Study 3, we seek to understand the mechanism underlying the information detail effect and test whether, as we predicted in H2, information detail reduces DCC through the serial mediation of perceived communication effectiveness and understanding the utility of providing personal data (Figure 1, Panel C; Table 1).

Method

Participants and study design. We recruited 178 participants (47.2% men; M_{age} = 33.37 years, *SD* = 10.66; 44.4% high school, 41.6% bachelor's degree, 12.4% master's degree, 1% PhD, 0.6% lower than high school) from Prolific to take part in a 12-minute study in exchange for money. Participants were randomly assigned to two information detail conditions (less detailed vs. detailed).

Procedure. All participants read the same description of Top-Fit, engaged in the same imagination task, and were exposed to the same instructions as in Studies 1 and 2. They were randomly assigned to one of the two manipulated conditions (less detailed vs. detailed information), which featured the appropriate stimuli from Study 2 (Appendix A). After reading the scenario, all participants completed measures of perceived communication effectiveness, understanding of the utility of providing personal data, DCC, familiarity with smart devices, manipulation checks for perceived information detail, perceived control (see Appendix C), and demographic information.

Results

Manipulation checks. The manipulation of information detail was successful (see Appendix B, Panel C, for means and standard deviations; information detail $t(176) = -4.47$, $p < .001$). Also, the control level was correctly perceived as high (> scale midpoint of 4) ($t(177) = 2.49$, $p = .014$; see Appendix B, Panel C).

Mediation analysis. To test our predictions, we first conducted a one-way ANCOVA to assess the effect of information detail on DCC and find significant effects (0 = less detailed information; 1 = detailed information). Specifically, the mean DCC level reported by respondents exposed to the detailed information condition ($M_{detailedinfo} = 4.65$, $SD = 1.78$) is significantly lower than the mean DCC level reported by those exposed to the less detailed information condition ($M_{lessdetailedinfo} = 5.29$, $SD = 1.58$; $F(1, 172) = 5.69$, $p = .018$, $\eta^2 = .032$) (see Table 4).

To assess the variables that we predict will explain the relationship between detailed information and DCC, we use a serial mediation model (Hayes, 2018, PROCESS model 6), with perceived communication effectiveness and understanding of the utility of providing personal data as mediators. In Table 5, we identify a significant serial indirect effect of information detail on DCC through perceived communication effectiveness and understanding of the utility of providing personal data ($b_{ind3} = -.32$, 95% confidence interval [CI]: -.50 to -.17), as well as a specific indirect effect through perceived communication effectiveness ($b_{ind1} = -.23$, 95% CI: -.46 to -.03). After accounting for these indirect effects, the direct effect of information detail on DCC is no longer significant ($b_{direct} = -.02$, 95% CI: -.47 to .42). Specifically, information detail predicts perceived communication effectiveness (path a_1; b = 1.17, $p < .001$), which predicts understanding of the utility of providing personal data (path d_{21}; b = .49, $p < .001$). The latter then reduces DCC (path b_2; b = -.56, $p < .001$). Perceived communication effectiveness also directly affects DCC (path b_1; b = -.20, $p = .02$).

The results of Study 3 thus support H2 and clarify that the reduction of DCC linked to detailed information stems from two indirect effects. The first is a serial mediation effect, such that a stronger perception of communication effectiveness increases understanding of the utility of providing personal data, which then reduces DCC. As communication effectiveness increases, consumers become more likely to understand why they would benefit from providing personal data. Then the second, indirect effect acknowledges that the reduction of DCC might result from communication effectiveness only, when understanding the utility of providing personal data is held constant.

Table 4. Effect of Information Detail on DCC - Tests of Between-Subjects Effects

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Intercept	148.692	1	148.692	53.325	< .001	.237
Gender	.377	1	.377	.135	.714	.001
Age	7.614	1	7.614	2.730	.100	.016
Education	1.527	1	1.527	.548	.460	.003
Familiarity with smart devices	11.619	1	11.619	4.167	.043	.024
Information detail	15.868	1	15.868	5.691	.018	.032
Error	479.609	172	2.788			

Table 5. Indirect Effects of Information Detail on DCC

Direct effects

Consequent

	Communication effectiveness				Understanding the utility of providing personal data				DCC			
	b (SE)	t	*p*	CI	*b* (SE)	t	*p*	CI	*b* (SE)	t	*p*	CI
Antecedent												
Constant	3.06 (.80)	3.84	< .001	[1.49, 4.63]	3.54 (.63)	5.63	< .001	[2.30, 4.79]	10.20 (.85)	12.05	< .001	[8.53, 11.87]
Information detail	a_1 1.17 (.22)	5.23	< .001	[.73, 1.61]	a_2 .06 (.18)	.30	.76	[-.30, .42]	b_{direct} -.02 (.23)	-.10	.92	[-.47, .42]
Communication effectiveness	—	—	—	—	d_{21} .49 (.06)	8.40	< .001	[.37, .60]	b_1 -.20 (.08)	-2.32	.02	[-.36, -.03]
Understanding the utility of providing personal data	—	—	—	—	—	—	—	—	b_2 -.56 (.09)	-5.92	< .001	[-.75, -.37]
Control variables												
Familiarity with smart devices	.15 (.09)	1.70	.09	[-.02, .32]	.12 (.07)	1.77	.08	[-.01, .25]	-.07 (.08)	-.78	.43	[-.23, .10]
Age	.01 (.01)	1.25	.21	[-.01, .04]	-.003 (.01)	-.39	.70	[-.02, .01]	-.02 (.01)	-1.53	.13	[-.04, .004]
Gender	.14 (.23)	.60	.55	[-.32, .59]	-.26 (.17)	-1.47	.14	[-.60, .09]	-.17 (.22)	-.80	.42	[-.60, .25]
Education	-.34 (.15)	-2.24	.03	[-.64, -.04]	-.14 (.12)	-1.18	.24	[-.37, .09]	-.11 (.15)	-.76	.45	[-.40, .18]
	$R^2 = .18$				$R^2 = .38$				$R^2 = .36$			
	$F(5, 172) = 7.75, p < .001$				$F(6, 171) = 17.26, p < .001$				$F(7, 170) = 13.83, p < .001$			

Indirect effects

	b (SE)	CI
Ind. 1: Information detail → Communication effectiveness → DCC	-.23 (.11)	[-.46, -.03]
Ind. 2: Information detail → Understanding the utility of providing personal data → DCC	-.03 (.09)	[-.22, .14]
Ind. 3: Information detail → Communication effectiveness → Understanding the utility of providing personal data → DCC	-.32 (.08)	[-.50, -.17]

Study 4: Information Detail and the Moderation of Type of Benefits

In Study 4, we predict that when consumers anticipate utilitarian or symbolic (hedonic) benefits, being exposed to detailed information does (not) decrease DCC, compared with exposures to less detailed information (Table 1; Figure 1, Panel D).

Method

Participants and study design. We recruited 433 participants (47.3% men; M_{age} = 30.28 years, *SD* = 10.97; 43.4% high school, 34.4% bachelor's degree, 16.9% master's degree, 3.5% PhD, 1.8% lower than high school) from Prolific to take part in a 12-minute study in exchange for money. Participants were randomly assigned to a 2 (information detail: less detailed vs. detailed information) × 3 (type of benefits: utilitarian vs. symbolic vs. hedonic) between-subjects design.

Procedure. All respondents read a passage introducing FitBand, a newly released smart band with a few basic apps and advanced fitness features that provide users with personalized nutrition recommendations. Respondents were asked to engage in an imagination task and picture themselves inside a consumer electronic store, staring at a FitBand and reading the instructions for using its fitness app. First, we manipulated the type of benefits (utilitarian vs. symbolic vs. hedonic) that these instructions promised consumers they could gain. Second, all respondents read a list of all the personal data that FitBand needs to generate personalized nutrition programs. Third, we manipulated the level of information detail that consumers receive regarding the functioning of its algorithm in processing users' data. The level of control was kept constant and high. Respondents thus were randomly assigned to one of the six conditions. The stimuli in Appendix A again had been pretested with a sample of 222 consumers who indicated, as expected, significant differences in their perceived information detail and perceived type of benefits. Consistent with our research design (i.e., control kept constant and high), the level of control reported was perceived as significantly higher than the scale midpoint (see Appendix B, Panel D). After reading the scenario, participants in each condition completed measures of DCC, familiarity with smart devices, manipulation checks for perceived information detail, types of benefits, and perceived control (see Appendix C), as well as their demographic information.

Results

Manipulation checks. The manipulations of information detail and type of benefits were successful. Respondents in the detailed information condition perceived the level of information as more informative and detailed, compared with those in the less detailed information condition. Respondents in the utilitarian (symbolic; hedonic) benefit condition perceived usage of FitBand as more beneficial for their health (image; enjoyment) than those in any other benefit condition (see Appendix B, Panel D, for means and standard deviations; information detail $t(431) = -4.92$, $p < .001$; utilitarian $F(2, 430) = 4.34$, $p = .014$; symbolic $F(2, 430) = 24.59$, $p < .001$; hedonic $F(2, 430) = 8.47$, $p < .001$). The control level was correctly perceived as high too ($t(432) = 7.05$, $p < .001$; see Appendix B, Panel D).

DCC. We validated our prediction using a between-subjects ANCOVA with DCC as the dependent variable and type of benefits (0 = utilitarian; 1 = symbolic; 2 = hedonic) as a moderator of the effect of information detail (0 = less detailed information; 1 = detailed information) on DCC. As we show in Table 6, Panel A, we uncover a significant main effect of information detail on DCC: The mean DCC level reported by respondents in the detailed information condition ($M_{detailedinfo} = 3.69$, $SD = 1.63$) is significantly lower than that reported by respondents in the less detailed information condition ($M_{lessdetailedinfo} = 4.71$, $SD = 1.61$; $F(1, 423) = 44.34$, $p < .001$, $\eta^2 = .095$). We find no significant main effect of type of benefits on DCC ($M_{utilitarian} = 4.25$, $SD = 1.77$; $M_{symbolic} = 4.37$, $SD = 1.74$; $M_{hedonic} = 3.99$, $SD = 1.55$; $F(2, 423) = 2.22$, $p = .110$, $\eta^2 = .010$). In Table 6, Panel A, and Figure 3, the information detail × type of benefits interaction is significant ($F(2, 423) = 10.01$, $p < .001$, $\eta^2 = .045$). A planned contrasts analysis also reveals that detailed information in the utilitarian ($M_{lessdetailedinfo} = 5.00$, $SD = 1.55$; $M_{detailedinfo} = 3.54$, $SD = 1.68$; $F(1, 423) = 30.09$, $p < .001$, $\eta^2 = .066$)

and symbolic ($M_{lessdetailedinfo}$ = 5.13, *SD* = 1.52; $M_{detailedinfo}$ = 3.58, *SD* = 1.61; $F(1, 423) = 33.91$, $p < .001$, $\eta^2 = .074$) benefit conditions decrease DCC; in the hedonic benefit condition, we find no changes in DCC level according to the level of information detail ($M_{lessdetailedinfo}$ = 4.02, *SD* = 1.54; $M_{detailedinfo}$ = 3.96, *SD* = 1.57; $F(1, 423) = .039$, $p = .843$, $\eta^2 = .000$) (see Table 6, Panel B). In support of H3, we thus confirm with Study 4 that the type of benefits moderates the effect of detailed information in terms of decreasing DCC. When consumers have detailed information, their DCC diminishes if they expect utilitarian or symbolic benefits from using FitBand. However, this effect vanishes when consumers anticipate hedonic benefits.

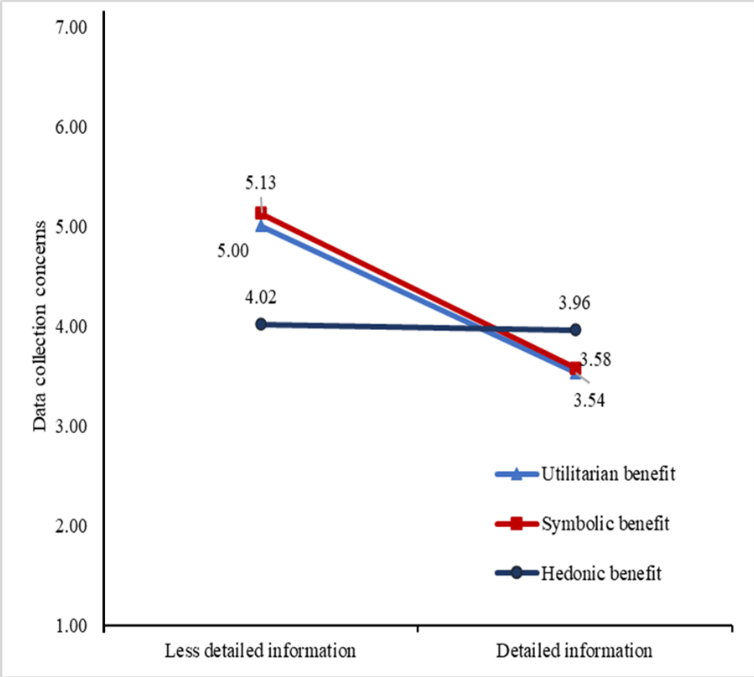
Table 6. Moderating Effect of Type of Benefits on the Relationship Between Information Detail and DCC

Panel A. Tests of Between-Subjects Effects						
Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Intercept	132.163	1	132.163	53.043	< .001	.111
Gender	2.241	1	2.241	.899	.344	.002
Age	6.468	1	6.468	2.596	.108	.006
Education	1.181	1	1.181	.474	.491	.001
Familiarity with smart devices	.000	1	.000	.000	.990	.000
Information detail	110.487	1	110.487	44.343	< .001	.095
Type of benefits	11.078	2	5.539	2.223	.110	.010
Information detail x Type of benefits	49.877	2	24.938	10.009	< .001	.045
Error	1053.956	423	2.492			

Panel B. Planned Contrasts Analysis Univariate Tests							
Type of benefits		Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Utilitarian	Contrast	74.962	1	74.962	30.086	< .001	.066
	Error	1053.956	423	2.492			
Symbolic	Contrast	84.479	1	84.479	33.905	< .001	.074
	Error	1053.956	423	2.492			
Hedonic	Contrast	.097	1	.097	.039	.843	.000
	Error	1053.956	423	2.492			

Each F tests the simple effects of Information detail within each level combination of the other effects shown. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.

Figure 3. Moderating Effect of Type of Benefit on the Relationship Between Information Detail and DCC



General Discussion

Even as we enter a new decade, one that was predicted to be the era of AI-enabled products, consumers remain reluctant to buy these products, seemingly due to their DCC (Berger-de Leon, Reinbacher, and Wee, 2018; Cisco, 2019; Insider Intelligence, 2020). A clear understanding of the factors that can inhibit DCC, in relation to AI-enabled products is therefore of pivotal importance. We focus on two relevant inhibitors: information detail and control. With four online, experimental studies, we demonstrate whether (Studies 1 and 2), how (Study 3), and when (Study 4) the combination of these two inhibitors can significantly diminish DCC.

Study 1 shows that providing consumers with detailed information lowers DCC, compared with providing no information; Study 2 affirms that detailed information reduces DCC the most, compared with not just no information but also information that is relatively less detailed. Study 1 also highlights the combined effect of information detail and control, such that control significantly moderates the diminishing effect of detailed information on DCC, strengthening this influence especially at high levels of consumer control but eliminating it when consumers lack control. In Study 3, keeping levels of control high and constant, we investigate the psychological mechanism underlying these effects to understand why consumers who get detailed information indicate lower DCC. The results reveal serial mediation: Detailed information increases consumers' perceptions of the effectiveness of the communication that explains the functioning of AI-enabled products' algorithms, and this communication effectiveness then increases their understanding of the utility of providing personal data, which reduces their DCC. The indirect effect of communication effectiveness is also significant. Finally, Study 4 defines boundary conditions for the observed effects. The type of benefits consumers anticipate from using AI-enabled products moderates the effect of detailed information on DCC, such that utilitarian and symbolic benefits magnify the effect of detailed information on DCC, whereas hedonic benefits nullify it.

Theoretical implications

Our research contributions are threefold. First, this study provides a clear understanding of the factors that can inhibit DCC in the context of AI-enabled products. We conceptually develop and empirically test a novel, previously untested combination of information detail and control, as DCC inhibitors. Extant research on consumers' privacy concerns mainly has focused on the control they possess (Malhotra, Kim, and Agarwal, 2004; Xu et al., 2012), but combining this sense of control with information detail can establish more effective strategies. We identify something similar to a placebo effect in the context of AI-enabled products, such that increasing consumers' literacy about AI-enabled products, by providing them with detailed information about how their algorithms work, reduces consumers' negative views of these objects, as manifested in DCC. Moreover, we qualify the level of detail, by comparing the effects of different levels of information detail on DCC. To the best of our knowledge, no previous study has provided such evidence in an AI context.

Second, we establish the psychological mechanism that can explain the relationship between information detail and DCC. Consumers' AI illiteracy increases DCC (Puntoni et al., forthcoming;

Rai, 2020), and in response to calls for more investigations of the psychological underpinnings of this effect, we propose and confirm an untested serial mediation process involving communication effectiveness (Sharma and Patterson, 1999) and interpretive inferences (Alba and Hutchinson, 1987). Detailed information increases the perceived effectiveness of communications about the algorithm's functioning, which helps consumers understand the utility of providing their personal data to inform AI-enabled products, which finally decreases their DCC.

Third, we provide novel evidence about the boundary conditions for the effect of information detail on DCC. We conceptually predict and empirically demonstrate that the diminishing effect of detailed information depends on the type of benefits consumers can gain from using AI-enabled products. Extant literature on AI-enabled products has focused on the role of benefits as antecedents of consumers' intentions to use (McLean and Osei-Frimpong, 2019), intentions to adopt (Rauschnabel, He, and Ro, 2018), or attitudes (Choi and Kim, 2016); we conceive of the type of benefits as a relevant boundary condition. Literature in the branding domain indicates that hedonic benefits can elicit positive feelings and distract consumers from negative stimuli (Park, Jaworski, and MacInnis, 1986; Park, MacInnis, and Priester, 2006); in parallel, we hypothesize and find a similar effect for AI-enabled products. Hedonic benefits reduce DCC, regardless of firm-initiated efforts to increase consumers' literacy about how AI-enabled products' algorithms work. To the best of our knowledge, no previous study has tested such considerations in an AI context.

Managerial implications

For companies and managers seeking to boost the mainstream diffusion of AI-enabled products, our study provides useful insights into whether, how, and when they can use business factors to decrease DCC. In particular, they need to account for the level of information detail and control when developing their communication strategies. When explaining how an AI-enabled product works, companies should provide consumers with detailed information about the underlying algorithms and how they process personal data, as well as explain that the data process is designed to produce the best (i.e., most personalized) outcome, to better meet their needs. In our results, providing consumers with such detailed information is the most effective solution by far. Offering less detailed information does little more than providing no information at all. At the same time though, companies must ensure that consumers feel confident in their full control over their personal data management, such as by enabling them to check easily what type of information is collected or to withdraw any information they choose from the company's database. Both relevant factors must be considered, in conjunction. A high level of control should always be accompanied by detailed information. Without sufficient control, detailed information cannot mitigate DCC.

A real-world example helps clarify this point. When we review the communication strategies adopted by smart watch and smart band brands (e.g., Xiaomi, Huawei, Samsung, and Fitbit), communication based on detailed information appears uncommon. Rarely do they provide a full explanation of the algorithms' functioning; instead, they offer missing, confusing, or fragmented information. In other industries, brands such as Facebook, Disney, and Apple have begun to explain how users' personal data are used in more detail, as well as offer full control over the information to users (Morey, Forbath, and Schoop, 2015). For example, on the Apple website, a separate section explains its privacy policy, specifying that customers have complete control over their data. It also details which data each app collects and how these data are managed. Thus for the Apple Music app, the explanation notes that personal data improve the company's understanding of consumer usage behavior, which helps Apple improve the app, customize users' experiences, and make recommendations that better reflect users' tastes. Will such a strategy pay off for Apple? Our results indicate it will, in that consumers should exhibit decreased DDC and be more willing to disclose their personal information when provided with such information.

We also caution companies against underestimating the role of the type of benefits offered. Once companies have established high levels of control and detailed information, they should frame the benefits that their AI-enabled products offer. Framing those benefits as utilitarian or symbolic, rather than hedonic, will help them maximize the DCC reduction they have achieved by emphasizing detailed information and high control. As much as possible, they should avoid (or be cautious about) communicating hedonic benefits, because doing so can jeopardize their other efforts to reduce DCC. When Fitbit and Apple highlight the utilitarian and symbolic benefits of their smart bands and watches, defining the devices as “designed to reach any fitness goals” or “stylish,” the strategy likely pays off for them. According to our results, these benefits further enhance the effect of detailed information and control for decreasing DDC and increasing consumers’ likelihood of disclosing personal information.

In conclusion, ensuring detailed information provision, high levels of customer control, and benefit framing that focuses on utilitarian and/or symbolic outcomes can create a win–win strategy for both consumers and companies. The former receive products and services that better meet their needs. The latter can mitigate DCC, encourage adoption, gather more data, and improve their offers.

Limitations and further research

Some limitations of this study provide avenues for continued research. First, with our experimental approach, we can test the hypotheses with some degree of generalizability, but to enhance the external validity of our findings, further research might replicate our study in other shopping settings or extend the investigation to other product categories, unlike smart trackers (e.g., smart home devices, smart cars, voice assistants). Second, we opted for an experimental approach to establish causality and ensure high levels of internal validity. We used fictitious brands to avoid potentially confounding influences (e.g., brand attitude, brand familiarity). However, consumers may express varying levels of DCC, depending on different brand-related factors (e.g., reputation, longevity, image), which in turn might moderate the effect of information detail and control on DCC. Third, our experiment protocol is based on an imagination task. We checked that the imaginary situation was realistic, but consumers arguably might not have encountered or heard about the AI-enabled product presented in the scenario. Additional research might include real shopping contexts to determine whether a decrease in DCC entails an actual increase in purchase intentions.

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Appendix

Appendix A: Product and Fitness App Descriptions as Stimuli

We report the stimuli, which apply to Studies 1 (pretest and main study), 2 (pretest and main study), and 3. The structure is as follows: Respondents read a description of the smart watch (i.e., Top-Fit), read the fitness app instructions, read the description of the algorithm's functioning, and finally read the description about the level of control over their personal data.

Study 1. Pretest and Main Study

No information and low control

Top-Fit is a new smart watch. It is a user-worn accessory (a band that is worn around the wrist) provided with artificial intelligence (integrated electronic and computing technologies).
Top-Fit gets calls, text messages and smartphone app notifications, it allows you to send quick replies, make contactless payments, store and play music. Top-Fit is equipped with sensors that track in real time the relationship between calories eaten and calories burned. Also, it is equipped with a microphone and a loudspeaker. Users can give Top-Fit voice commands, and it provides them with voice and/or text message feedbacks. Moreover, Top-Fit can provide users with personalized nutrition recommendations and healthy meal plans that can help users to improve their personal health significantly.

This is Top-Fit. In order to create a personalized food plan in line with your health-goals, Top-Fit needs your information about:

• age
• gender
• ethnicity
• education
• job
• place of residence
• marital status
• number of sons and/or daughters
• time available for cooking
• cooking skills
• diet and food habits
• food preferences
• physical activity
• sleep quality and duration
• level of stress
• bodyweight
• BMI (body mass index)
• genetic family history
• drugs
• blood pressure
• heart rate
• glucose level

• liver function

• kidney function.

The more Top-Fit knows about you the most effective food plan can be expected.

You will not keep full control over the management of your personal information. For example, you can decide which information you want to delete, but for some reasons (legal reasons or to prevent harm) Top-Fit can decide to preserve some of your data stored in the backup systems.

Detailed information and low control

Top-Fit is a new smart watch. It is a user-worn accessory (a band that is worn around the wrist) provided with artificial intelligence (integrated electronic and computing technologies).
Top-Fit gets calls, text messages and smartphone app notifications, it allows you to send quick replies, make contactless payments, store and play music. Top-Fit is equipped with sensors that track in real time the relationship between calories eaten and calories burned. Also, it is equipped with a microphone and a loudspeaker. Users can give Top-Fit voice commands, and it provides them with voice and/or text message feedbacks. Moreover, Top-Fit can provide users with personalized nutrition recommendations and healthy meal plans that can help users to improve their personal health significantly.

This is Top-Fit. In order to create a personalized food plan in line with your health-goals, Top-Fit needs your information about:

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• gender

• ethnicity

• education

• job

• place of residence

• marital status

• number of sons and/or daughters

• time available for cooking

• cooking skills

• diet and food habits

• food preferences

• physical activity

• sleep quality and duration

• level of stress

• bodyweight

• BMI (body mass index)

• genetic family history

• drugs

• blood pressure

• heart rate

• glucose level

• liver function

• kidney function.

The more Top-Fit knows about you the most effective food plan can be expected.

Knowing your personal data and those of other users with similar characteristics and goals, Top-Fit's algorithm improves its speed of learning and its abilities to respond to your needs.

You will not keep full control over the management of your personal information. For example, you can decide which information you want to delete, but for some reasons (legal reasons or to prevent harm) Top-Fit can decide to preserve some of your data stored in the backup systems.

No information and high control

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Detailed information and high control

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Study 2. Pretest and Main Study

No information and high control: as in Study 1.

Less detailed information and high control

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The more Top-Fit knows about you the most effective food plan can be expected.

Top-Fit's hybrid algorithm is able to respond to your needs.

You will keep full control over the management of your personal information. For example, at any time you can decide which information you want to delete and Top-Fit will delete them from the backup systems immediately.

Detailed information and high control: as in Study 1.

Study 3

Less detailed information and high control: as in Study 2.

Detailed information and high control: as in Study 1 and Study 2.

Study 4. Pretest and Main Study

We report the stimuli, which apply to Study 4 (pretest and main study). The structure is as follows: Respondents read a description of the smart band (i.e., FitBand), read the description of the benefit consumers can gain using the smart band, read the fitness app instructions, read the description of the algorithm's functioning, and finally read the description about the level of control over their personal data.

Less detailed information, utilitarian benefits, and high control

FitBand is a new smart band. It is a user-worn accessory (a band that is worn around the wrist) provided with artificial intelligence (integrated electronic and computing technologies).
FitBand is provided with few basic apps, such as calendar app, weather app, music app, and several health and fitness apps that can track sleep, fitness, and nutrition. FitBand is equipped with sensors that track in real time the relationship between calories eaten and calories burned. Also, it is equipped with a microphone and a loudspeaker. Users can give FitBand voice commands, and it provides them with voice and/or text message feedbacks. Moreover, FitBand can provide users with personalized nutrition recommendations and healthy meal plans that can help users to eat healthier.

Eating healthy following FitBand's nutritional recommendations is a useful and easy activity. People use the personalized nutritional recommendation program of FitBand to prevent the occurrence of health issues related to bad nutrition (e.g., obesity, high blood pressure, heart disease etc.).

This is FitBand. In order to create a personalized food plan in line with your health-goals, FitBand needs your information about:

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The more FitBand knows about you the most effective food plan can be expected.

FitBand's hybrid algorithm is able to respond to your needs.

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Detailed information, utilitarian benefits, and high control

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The more FitBand knows about you the most effective food plan can be expected.

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Less detailed information, symbolic benefits, and high control

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The more FitBand knows about you the most effective food plan can be expected.

FitBand's hybrid algorithm is able to respond to your needs.

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Knowing your personal data and those of other users with similar characteristics and goals, Top-Fit's algorithm improves its speed of learning and its abilities to respond to your needs.

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Less detailed information, hedonic benefits, and high control

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Eating healthy following FitBand's nutritional recommendations is an enjoyable and sensational activity. People use the personalized nutritional recommendation program of FitBand for its fun (e.g., feeling excited about using it).

This is FitBand. In order to create a personalized food plan in line with your health-goals, FitBand needs your information about:

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The more FitBand knows about you the most effective food plan can be expected.

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Knowing your personal data and those of other users with similar characteristics and goals, Top-Fit’s algorithm improves its speed of learning and its abilities to respond to your needs.

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Appendix B: Pretest and Manipulation Checks

Panel A: Study 1 – Pretest and Main Study

Independent sample T-test for Information Detail and Control

		Study 1							
		Pretest				Manipulation checks			
	Condition	M (SD)	t-value	df	Sig.	M (SD)	t-value	df	Sig.
Information detail	No information	3.81 (1.71)	-4.59	198	< .001	3.80 (1.64)	-6.76	358	< .001
	Detailed information	4.87 (1.54)				4.91 (1.47)			
Control	Low control	2.55 (1.41)	-9.95	198	< .001	2.70 (1.55)	-9.62	358	< .001
	High control	4.76 (1.72)				4.31 (1.64)			

Panel B: Study 2 – Pretest and Main Study

One-way ANOVA for Information Detail and One-sample T-test for Control

		Study 2							
		Pretest				Manipulation checks			
	Condition	M (SD)	F-value	df	Sig.	M (SD)	F-value	df	Sig.
Information detail	No information	3.94 (2.18)	12.08	2, 125	< .001	3.14 (1.38)	18.40	2, 209	< .001
	Less detailed information	4.35 (1.95)				4.74 (1.59)			
	Detailed information	5.70 (0.91)				3.98 (1.65)			
		M (SD)	t-value	df	Sig.	M (SD)	t-value	df	Sig.
Control*	High control	4.80 (1.39)	6.46	127	< .001	4.57 (1.59)	5.22	211	< .001

*****Respondents also completed a four-item scale (see Appendix C; Martin et al., 2017) to indicate their perception of the level of control their have over their personal data according to the smart watch's description. Since we kept constant the control condition, providing respondents only with high-level control condition based on the results of Study 1, we conducted a one-sample t-test in order to check if the mean level of the perception of the level of control was above the scale midpoint (i.e. 4). Respondents on average perceived the level of control reported in the description as significantly higher than the scale midpoint value.

Panel C: Study 3 – Main Study

Independent sample T-test for Information Detail and One-sample T-test for Control

	Study 3				
	Manipulation checks				
	Condition	M (SD)	t-value	df	Sig.
Information detail	Less detailed information	3.14 (1.57)	-4.47	176	< .001
	Detailed information	4.19 (1.54)			
Control*	High control	4.29 (1.58)	2.49	177	.014

*****Respondents also completed a four-item scale (see Appendix C; Martin et al., 2017) to indicate their perception of the level of control their have over their personal data according to the smart watch's description. Since we kept constant the control condition, providing respondents only with high-level control condition based on the results of Study 1, we conducted a one-sample t-test in order to check if the mean level of the perception of the level of control was above the scale midpoint (i.e. 4). Respondents on average perceived the level of control reported in the description as significantly higher than the scale midpoint value.

Panel D: Study 4 – Pretest and Main Study

One-way ANOVA for Type of Benefits, Independent sample T-test for Information Detail, and One-sample T-test for Control

		Study 4								
			Pretest				Manipulation checks			
		Condition	M (SD)	F-value	df	Sig.	M (SD)	F-value	df	Sig.
	Utilitarian	Utilitarian	5.67 (0.84)				5.46 (1.19)			
		Symbolic	5.33 (0.75)	4.44	2, 219	.013	5.10 (1.08)	4.34	2, 430	.014
		Hedonic	5.32 (0.81)				5.13 (1.11)			
	Symbolic	Utilitarian	2.81 (1.44)				2.51 (1.34)			
Type of benefits		Symbolic	4.48 (1.70)	21.25	2, 219	< .001	3.62 (1.79)	24.59	2, 430	< .001
		Hedonic	3.53 (1.58)				2.59 (1.31)			
	Hedonic	Utilitarian	4.57 (1.34)				4.37 (1.16)			
		Symbolic	4.34 (1.49)	12.95	2, 219	< .001	4.27 (1.13)	8.47	2, 430	< .001
		Hedonic	5.39 (1.05)				4.79 (1.14)			
			M (SD)	t-value	df	Sig.	M (SD)	t-value	df	Sig.
	Information detail	Less detailed information	4.27 (1.79)	-3.22	220	.001	3.74 (1.70)	-4.92	431	< .001
		Detailed information	5.00 (1.57)				4.50 (1.50)			
	Control*	High control	4.87 (1.56)	8.36	221	< .001	4.46 (1.35)	7.05	432	< .001

*****Respondents also completed a four-item scale (see Appendix C; Martin et al., 2017) to indicate their perception of the level of control their have over their personal data according to the smart watch's description. Since we kept constant the control condition, providing respondents only with high-level control condition based on the results of Study 1, we conducted a one-sample t-test in order to check if the mean level of the perception of the level of control was above the scale midpoint (i.e. 4). Respondents on average perceived the level of control reported in the description as significantly higher than the scale midpoint value.

Appendix C: Construct Operationalization and Measurement

Construct	Operationalization	Measurement (Source)	Cronbach's alpha α or *r*
Communication effectiveness	1. Top-Fit keeps me well informed about how the algorithm works to respond to my needs. 2. Top-Fit explains in a meaningful way how the algorithm processes my personal data. 3. Top-Fit provides me with clear information about how the algorithm works. 4. Top-Fit explains to me how data are used to improve the algorithm abilities to respond to my needs. 5. Top-Fit informs me about how the algorithm works in an easy-to-understand manner.	Five 7-point items anchored by “strongly disagree” [1] and “strongly agree” [7], adapted from Sharma and Patterson (1999); Auh, Bell, McLeod, and Shih (2007).	Study 3: α = .96
Understanding the utility of providing personal data	1. I am aware of the utility of providing my personal data.* 2. I understand the value of providing my personal data. 3. I understand why is important to provide my personal data. 4. I recognize the relevance of providing my personal data.	Four 7-point items anchored by “strongly disagree” [1] and “strongly agree” [7], adapted from Escalas and Stern (2003).	Study 3: α = .95
Data collection concerns (DCC)**	1. When Top-Fit asks me for personal information, I should think twice before providing it.*[Study 1 and Study 3] 2. It bothers me to give personal information to Top-Fit. 3. I am concerned that Top-Fit collects too much personal information about me.	Three 7-point items anchored by “strongly disagree” [1] and “strongly agree” [7], adapted from Smith, Milberg, and Burke (1996).	Study 1: α = .92 Study 2: α = .90 Study 3: α = .93 Study 4: α = .91
Manipulation checks **			
Information detail		Two 7-point items anchored by:	
	1. Concerning Top-Fit's algorithm, the description I read contained: 2. Concerning Top-Fit's algorithm, the description I read was:	“Very little information about the algorithm used and its functioning” [1] / “A lot of information about the algorithm used and its functioning” [7] “Not at all detailed” [1] / “Very detailed” [7], adapted from Gleim, Smith, Andrews, and Cronin (2013).	Pretest Study 1: α = 0.78 Study 1: α = 0.86 Pretest Study 2: α = 0.93 Study 2: α = 0.93 Study 3: α = 0.87 Pretest Study 4: α = 0.87 Study 4: α = 0.88
Control	1. I believe I have control over what happens to my personal and nutritional information. 2. It is up to me how much Top-Fit uses my personal and nutritional information. 3. I have a say in how my personal and nutritional information is used by Top-Fit. 4. I have a say in whether my personal and nutritional information is shared with others.	Four 7-point items anchored by “strongly disagree” [1] and “strongly agree” [7], adapted from Martin, Borah, and Palmatier (2017).	Pretest Study 1: α = .93 Study 1: α = .92 Pretest Study 2: α = .81 Study 2: α = .90 Study 3: α = .90 Pretest Study 4: α = .92 Study 4: α = .84

Utilitarian benefits	1. Using FitBand is a convenient way to prevent the occurrence of health issues related to bad nutrition. 2. Following FitBand's nutritional recommendations makes eating healthy an easier task.*Study 4 3. Following FitBand's nutritional recommendations is useful to prevent the occurrence of health issues related to bad nutrition.	Three 7-point items anchored by "strongly disagree" [1] and "strongly agree" [7], adapted from McLean and Osei-Frimpong (2019).	Pretest Study 4: α = .76 Study 4: α = .86
Symbolic benefits	1. Using FitBand's nutritional recommendation program enhances my image towards others. 2. Using FitBand's nutritional recommendation program makes me seem more valuable than others. 3. Using FitBand's nutritional recommendation program is a status symbol for me. 4. Using FitBand's nutritional recommendation program makes me seem more prestigious than those who do not.	Four 7-point items anchored by "strongly disagree" [1] and "strongly agree" [7], adapted from McLean and Osei-Frimpong (2019).	Pretest Study 4: α = .93 Study 4: α = .91
Hedonic benefits	1. I find using FitBand's nutritional recommendation program is enjoyable. 2. The actual process of using FitBand's nutritional recommendation program is sensational. * Pretest Study 4 3. I have fun using FitBand's nutritional recommendation program to eat healthy.	Three 7-point items anchored by "strongly disagree" [1] and "strongly agree" [7], adapted from McLean and Osei-Frimpong (2019).	Pretest Study 4: α = .91 Study 4: α = .82
Control variable			
Familiarity with smart devices	1. In general, would you consider yourself unfamiliar or familiar with smart devices? *Study 3 2. Would you consider yourself uninformed or informed about smart devices? 3. Would you consider yourself knowledgeable about smart devices?	Three 7-point items, anchored by "very unfamiliar" [1] and "very familiar" [7], "not at all informed" [1] and "highly informed" [7], "know nothing at all" [1] and "know a great deal" [7] adapted from Oliver and Bearden (1985).	Study 1: α = .90 Study 2: α = .93 Study 3: α = .95 Study 4: α = .91

*Items delated after scale reliability test.
**Items in both the Pretest of Study 4 and Study 4 referred to FitBand instead of Top-Fit.

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“I’m Sorry Dave, I’m Afraid I Can’t Do That”:

Non-User Fears of Negative Social Roles in the Consumer-Smart Object Relationships

Introduction

Smart objects (SOs) are physical objects and services provided with Internet connectivity and artificial intelligence (AI), that can interact with the user and other SOs by exercising agency, autonomy, and authority (Novak & Hoffman, 2019). The use of SOs is now embedded in people’s everyday lives. Consumers resort to using SOs when, among many other activities, they ask their smartphone or their smart car what is the fastest route to a certain destination, check their fitness activity on their smartwatches, choose movies on Netflix, ask Alexa to turn on or off the lights, to schedule meetings, and to set alarms. Despite this pervasive presence and variety of occasions for use, consumers’ adoption of SOs is still in its infancy. Indeed, while past market forecasts predicted that SOs should have reached the mainstream adoption in 2020 (Gartner, 2018), actual figures show a less prosperous scenario. Out of the 50 billion devices connected to the Internet by 2020, only 20 billion devices are in play as of today (Kranz, 2019). From the consumer perspective, several reasons are at the origin of this inconsistency. Specifically, consumers can avoid or delay the adoption of SOs because of functional (e.g., use complexity, risk, object intrusiveness), psychological (e.g., concerns of becoming dependent on SO, low usage self-efficacy), and individual barriers (e.g., individuals’ predisposition to reject change) (Chouk & Mani, 2019; Mani & Chouk, 2017, 2018, 2019; Sundaresan Ram & Sheth, 1989).

All these barriers stem from either SO technical capacities (e.g., connectivity, ubiquity, and smartness) or consumers’ personal traits. Focusing on SO capacities, they depend on both SO technical abilities (e.g., being provided with Internet connection, sensors, AI systems) as well as human-like characteristics (e.g., usage of natural language to communicate with the user, having humanized names and genders, and ability to interact with the user in real time). In this paper we will focus on the latter, as the human-like characteristics enhance the SO's social aspect, making SOs' social presence more salient (McLean & Osei-Frimpong, 2019). The relevance of SOs' social aspect is underlined also by companies in the industry when positioning their products. For example, in their ads, Google and Amazon depict their digital voice assistants (i.e., Google Home and Alexa) as social actors, such as an assistant that helps an old man to recall the memories he has about his wife[1]. This social aspect has affected how consumers interact with the SO. Indeed, consumer-SO interactions have acquired meaning that extend beyond the utilitarian benefits stemming from SO technical capacities, as SO characteristics are enriched by social aspects. The motivation leading consumers to use SOs now involves this social aspect. People not only use SOs as electronic devices, they use them for social purposes such as conversation (Ammari, Kaye, Tsai, & Bentley, 2019) or having company (Gao, Pan, Wang, & Chen, 2018). These characteristics lead consumers to look at SOs as potential partners in a relationship that can be referenced to social and interpersonal relationships (Gao et al., 2018; Hoffman & Novak, 2018; Novak & Hoffman, 2019). People can compare SOs to their romantic companions (Gao et al., 2018) and also attribute to them social roles (e.g., partner, master, or servant - Schweitzer et al., 2019). As the consumer-SO interaction evolution has implications for consumer behavior (e.g., changes in the occasions of use and type of task performed), it has also implications for consumers' resistance to the adoption of SOs. To explain how the relational dimension of consumer-SO interactions can affect consumer resistance, we resort to interpersonal relationship literature. According to this stream of literature, people can decide to not enter into an intimate relationship because of negative aspects and risks that the relationship itself can entail (Hatfield, 1984; Reis, 1990; Reis & Shaver, 1988). However, consumer resistance frameworks have not included the relational perspective as a barrier that can explain this phenomenon so far. In order to fully understand why a consumer rejects a SO, it is necessary to account for reasons that may stem from consumers' perception of a SO as potential partner in a relationship.

This article aims at enriching the framework of consumer resistance to the adoption of SOs by providing a new category of barriers. This new category refers to the possibility that the consumer imagines a future relationship with a SO and attaches negative aspects and risks to that relationship. Through an exploratory qualitative study, we show that in addition to functional, psychological, and individual barriers, consumers avoid the adoption of a SO also because of relational barriers. This work also contributes to the literature on consumer-SO relationships in two ways. First we examine consumer-SO relationships, adopting an anticipatory approach: We analyze non-users' perspective about a potential relationship, rather than their opinion about an ongoing relationship. Second, we shed light on SOs' negative social roles that have been mostly under-investigated, by uncovering several new ones according to interpersonal relationship literature.

Theoretical Framework

Resistance to Innovations

Marketing literature that explains the consumer rejection of innovation phenomenon is the one about consumer resistance to innovation (Heidenreich & Handrich, 2015; Kim & Kankanhalli, 2009; Lapointe & Rivard, 2005; Ram, 1989; Ram & Sheth, 1989). According to Ram and Sheth (1989, p.6)consumers may manifest resistance, even if they consider the innovation as necessary and desirable, "either because it poses potential changes from a satisfactory status quo or because it conflicts with their belief structure." Several studies empirically examine the resistance in different innovative contexts, including SOs (Claudy, Garcia, & O'Driscoll, 2015; Mani & Chouk, 2017), and smart services (Chouk & Mani, 2019; Claudy et al., 2015; Laukkanen, 2016; Laukkanen, Sinkkonen, Kivijärvi, & Laukkanen, 2007; Mani & Chouk, 2018, 2019). Such studies generally use the Ram and Sheth (1989) model as a theoretical framework to identify barriers leading to consumer resistance to a specific innovation. The application of the original model, in some cases, led to the extension of the primary framework based on the identification of new situational barriers, categorized as either functional barriers (e.g., use complexity, risk, object intrusiveness) or psychological barriers (e.g., concerns of becoming dependent on SOs, low usage self-efficacy). The recent work of Mani and Chouk (2018) about consumer resistance is the most relevant update of Ram and Sheth's (1989) model from both an empirical and theoretical perspective. The authors apply Ram and Sheth's (1989) model to the smart service context and theoretically extend it, taking into account two new key factors that can lead consumers to avoid the adoption of smart services. First, Mani and Chouk (2018) include variables related to situational factors, such as new technical capacities of smart services (e.g., smartness, connectivity, autonomy, and ubiquity) that affect individuals' attitudes and beliefs toward smart technologies (i.e., technological vulnerability barrier and skepticism). Second, they include a variable related to individual traits (i.e., individuals' predisposition to reject change), that does not depend on situational factors. The adaptation and subsequent extension of the original model result in the systematization of three main categories of barriers to the adoption of smart services: functional, psychological, and individual. Functional barriers occur when "consumers perceive significant changes from adopting the innovation" (Sundaresan Ram & Sheth, 1989, p. 7) and are caused by innovation characteristics (Mani & Chouk, 2017, 2018). Indeed, in the SO domain, consumers may express resistance because they perceive high use complexity, high security risk, high health risk (Mani & Chouk, 2018), and high object intrusiveness (Mani & Chouk, 2017). Psychological barriers occur when the adoption of the innovation is in "conflict with customers' prior beliefs" (Sundaresan Ram & Sheth, 1989, p. 7) and are caused by characteristics that consumers show toward the innovation. Indeed, in the SO realm, consumers may express resistance because when they think about the innovation, they experience self-image incongruence, need for human interaction, technological dependence, technological anxiety, skepticism (Mani & Chouk, 2018), and privacy concerns (Chouk & Mani, 2019; Mani & Chouk, 2019). Finally, individual barriers (Mani & Chouk,

2018) refer to a specific personal trait of each individual, i.e., an individual's tendency to prefer the status quo over any novelty, thereby rejecting change.

Mani and Chouk's (2018) work is mainly driven by the need to account for consumers' attitudes and beliefs toward smart services that are affected by the new technical capacities of these products and services. However, the technological development of SOs is not only represented by the improvement of their technical capacities. Indeed, it also consists in the improvement of specific characteristics that aim at making a SO look like a human being (e.g., usage of natural language to communicate with the user, having humanized name and gender, and having the ability to interact with the user in real time – Feine, Gnewuch, Morana, & Maedche, 2019). These characterisitcs make it easy for individuals to anthropomorphize the SO (Belk & Kniazeva, 2018; Hoffman & Novak, 2018), thereby strongly modifying the quality of the consumer-SO interaction. More importantly, consumers look at and interact with SOs as though they are potential parters in a relationship (Gao et al., 2018; Garg & Moreno, 2019; Lopatovska & Williams, 2018; Purington, Taft, Sannon, Bazarova, & Taylor, 2017). Although Mani and Chouk's (2018) framework provides a relevant contribution to explain the resistance in the digital landscape, some consumer resistance aspects are still uncovered. Indeed, considering the fact that consumers can see SOs as potential partners in a relationship, Mani and Chouk's (2018) taxonomy falls short in explaining consumer resistance. In this paper, we argue that as new technical capacities entail some dark sides that evolve in new specific barriers to the adoption of smart services (e.g., technological vulnerability barrier, and skepticism - Mani & Chouk, 2018), so may the relational aspect. In order to explore this possibility, the anthropomorphic and social aspects of SOs need to be analyzed further.

SOs as Potential Partners

SOs embed specific human-like characteristics that allow them to elicit a social presence (McLean & Osei-Frimpong, 2019), thereby leading the individual to personify them (Gao et al., 2018;

Garg & Moreno, 2019; Hoffman & Novak, 2018; Lopatovska & Williams, 2018; Purington et al., 2017). Individuals, thus, see a SO as something more than an electronic device (e.g., they perceive the SO as having its own mind - Shank, Graves, Gott, Gamez, & Rodriguez, 2019) and this has consequences on how people use SOs. Specifically, people not only use SOs as electronic devices, they also use them for social purposes, such as conversation (Ammari et al., 2019) or having company (Gao et al., 2018). Various literature across a wide variety of disciplines, such as consumer–brand relationships (Fournier, 1998); CASA paradigm ("computers are social actors" - Reeves & Nass, 1996); HCI (human-computer interaction - Culley & Madhavan, 2013; Shneiderman et al., 2016); and HRI (human-robot interaction - Goodrich & Schultz, 2007) established that the anthropomorphization of inanimate entities is the basis for individuals setting up a relationship with an object (i.e., brand, SO), and that these relationships can be referenced to social and interpersonal relationships. Specifically, in the SO domain, Novak and Hoffman (2019) have conceptualized specific types of consumer-SO relationships (i.e., consumer as master-SO as servant, consumer as servant-SO as master, and partner). This conceptualization has been supported and deepened by empirical studies, both qualitative (Gao et al., 2018; Schweitzer et al., 2019) and quantitative (Kang & Kim, 2020; Sundar, Jung, Waddell, & Kim, 2017; Wang & Krumhuber, 2018; Wu, Chen, & Dou, 2017), that enriched the social roles individuals assign to SOs (e.g., servant, assistant, partner, master, family member, and engineer). Relationships that individuals establish with brands and SOs can be analyzed based on several dimensions, such as communality, agency, and power equality (Fournier & Alvarez, 2013; Novak & Hoffman, 2019). Among others, a dimension is valence (i.e., whether a given relationship is positive or negative in tonality and experience - Iacobucci & Ostrom, 1996; Wish, Deutsch, & Kaplan, 1976). In the branding literature, Fournier and Alvarez (2013) shed light on the relevance of valence in characterizing consumer-brand relationships. The authors argue that analyzing the features of negatively-valenced relationships can help to understand how these kinds of relationships can affect consumers' attitudes and behaviors toward brands. Moreover, in their work, they provide a plethora of negative consumer-brand relationships and respective brands' negative social roles. On the contrary, relationships with negative valence have been investigated much less in the SO domain. Indeed, there is only preliminary evidence of the negative social role of a SO when it is perceived as a master, i.e., when consumers struggle to successfully interact with SOs that are difficult to control or, for example, have a difficult time understanding voice command (Novak & Hoffman, 2019; Schweitzer et al., 2019). In this article, we propose that, as it happens with brands, negative consumer-SO relationships can also affect consumers' attitudes and behaviors toward SOs. More importantly, as we are in the context of consumers' resistance, we argue that the anticipation of a future negative relationship with a SO, and the negative social roles of the SO, can lead consumers to experience resistance. In order to better explain this passage, we resort to interpersonal relationship literature. In particular, we use the fear of intimacy construct.

Consumer-SO Relationship and Fear of Intimacy

When we talk about interpersonal relationships we deal with intimacy. This process is typical of a lot of different interpersonal relationships, especially the more valuable and supportive ones (Reis, 1990). However, despite its positive effects (Reis & Shaver, 1988), intimacy is a double-edged sword. Indeed, it exposes the individual to a state of vulnerability (Reis, 1990). Because of this reason, people can be reluctant to start a relationship in which the intimacy process occurs (Reis, 1990), experiencing the fear of intimacy. The fear of intimacy can be fed by different kinds of fear, such as the fear of exposure or abandonment, fear of loss of control, or loss of individuality (Hatfield, 1984).

The fear of intimacy involves relationships with others that are considered valuable (Descutner & Thelen, 1991) but that can be inhibited by the perception of risks and bad consequences that may originate from the relationship itself (Bartholomew, 1990; Pilkington & Richardson, 1988). This mechanism is similar to the one that explains consumer resistance to innovations, according to which, consumers reject some innovations that they consider necessary and desirable because of the presence of negative aspects and risks entailed by the adoption (Sundaresan Ram & Sheth, 1989). Therefore, in this context, the fear of intimacy construct can give interesting insights into understanding the resistance to SO for managers that want to convert people interested in these new types of technologies, but who are reluctant to finalize the purchase.

Another analogy between interpersonal relationships and the way consumers interact with SOs is about the exchange of valuable information. Self-disclosure, which is an important characteristic of intimate interpersonal relationships (Descutner & Thelen, 1991; Reis & Shaver, 1988), can also lead to a closer connection between the consumer and a SO (Li & Rau, 2019). As it happens in the interpersonal domain when individuals experience the fear of intimacy in respect to the decision to create a relationship with another individual, consumers can resist adopting a SO because of the fear they experience when they think of the negative aspects and risks that are involved with an intimate relationship.

In the resistance taxonomy about barriers illustrated above, functional barriers are about innovation characteristics, while psychological barriers and individual barriers are about consumer characteristics (Mani & Chouk, 2017, 2018). Thus, all these barriers are based on a unilateral perspective of the resistance phenomenon. The consumer resistance paradigm does not contemplate the idea that the consumers can see the object of the resistance as a partner with which they can start a relationship in the future. However, considering the fact that SOs can be seen as potential partners in a future relationship, the unilateral perspective about resistance may lead to a partial vision of the phenomenon. The framework composed by the results of functional, psychological, and individual barriers are, indeed, incomplete and shows a gap for a new kind of barrier that needs to be investigated: The relational barrier, which may be about the fear of intimacy that consumers experience when they think about entering into a relationship with a SO. In order to understand whether the relational barrier can exist, this study aims at understanding what are the threats (i.e., the negative aspects and risk) that consumers associate to a possible relationship with a SO, and what kind of fears follow these threats, preventing consumers from entering into a relationship with a SO.

Method

To accomplish the objective of this study, we adopted a qualitative approach based on in-depth individual interviews. As discussed above, SOs present some human-like characteristics that make it easy for consumers to consider them as potential partners. This introduces the possibility of the existence of a new category of barriers to consumers' adoption of SOs: the relational barrier. This barrier has not been investigated in the resistance to innovation literature so far. Therefore, we decided to adopt a qualitative approach in order to let respondents freely speak about the thoughts and emotions hindering them from entering into a relationship with a SO, rather than providing them with some elements selected a priori by the researchers (Belk, Fischer, & Kozinets, 2012; Maxwell, 2012). Our decision also stems from the fact that qualitative method has frequently been used in the study of consumers and technology, especially when the research aims at studying topics that are hidden and sensitive to consumers (Deutsch, Erel, Paz, Hoffman, & Zuckerman, 2019; Guzman, 2019; Lee, McGoldrick, Keeling, & Doherty, 2003; Mick & Fournier, 1998; Touzani, Charfi, Boistel, & Niort, 2018). Asking participants to understand and describe their inner reasons and emotions that prevent them from entering into a relationship with a SO is an objective of that kind.

Time Period

Data for the study was collected in Italy in January 2018. Place and timing of this study are important because it took place before the launch of the main digital voice assistants (i.e., Amazon Echo, Google Home, and Apple HomePod) in the Italian market and when more than the half of the population owned a number of smart devices per capita between zero and two (Statista, 2018).

However, in that moment, most people were using a smartphone and were aware of what a smart device is (e.g., smart TV, smartwatch, and digital voice assistant). This depicts an environment in which although most consumers are aware of these technologies, their knowledge lacks direct experience with SOs. These characteristics made the Italian market a perfect environment to study consumers' resistance to SOs: Consumers were sufficiently aware about SOs to be able to consider them as potential partners, however most of them didn't own any SOs but the traditional ones (i.e., smartphone, laptop, and tablet). Therefore, we decided to conduct the study with a sample of Italian consumers.

Participants

Participants in this study were 33. They ranged in age from 22 to 58 with a mean age of 29.82 (SD = 11.17), 55 percent male and 45 percent female, with a medium-high education level (30 percent with a high school diploma, 67 percent with bachelor's and master's degrees, and 3 percent with a PhD). They were all Italians living in Italy and all SO non-users. Given the specificity of the research topic, the adoption of a convenience sampling procedure was considered the best choice in order to select respondents. Indeed, we decided to focus on a precise type of SO non-users: The ones who saw SOs as potential partners but, for some reasons, decided to not own them.

Procedure

Interviews were conducted according to the Zaltman Metaphor Elicitation Technique (ZMET), which is a hybrid methodology that integrates projective techniques with semi-structured in-depth interviews to help respondents provide narratives to explain their ideas, feelings, and perceptions of particular phenomena (Zaltman, 1997; Zaltman & Coulter, 1995).

The data collection process started by providing respondents with information about the topic of the research: "Reasons hindering consumers to enter in a relationship with SOs even if they consider them as potential partners," in order to guide them to think about it. Next, respondents were requested to collect, prior to the individual interviews, at least 10 images, from any source, that they felt said something personal and significant about the topic of the research. All respondents searched for images online and brought them to the interview, during which they showed their images to the interviewer through the help of either a computer or a smartphone. These images provided the stimuli for the ZMET interviews. Each interview was conducted in a manner of a guided conversation for approximately 45 minutes and followed the ZMET steps. Specifically, as outlined by Zaltman and Coulter (1995), the current research has taken the approach of applying nine steps, since they are considered to be appropriate for the purpose of the research. They are "storytelling," "missed images," "sorting task," "construct elicitation," "most representative image," "opposite image," "sensory images," "mental map," and "summary image." For example, the "sorting task" consisted in having the respondent organize his or her images into meaningful groups and to provide a label or description for each group, whereas the "most representative image" involved the selection of the image that, according to each respondent, was the most illustrative and meaningful in representing the reasons that prevented the relationship. Once all the interviews were completed, transcripts of the interviews were produced for data analysis.

An important advantage of this technique is that the search and selection process required by ZMET to generate the visual stimuli necessary for the interview helps respondents commit to the research topic and feel involved in it. This can lead to a deeper and more meaningful discussion during the interview (Zaltman, 1997). Moreover, as stressed by Lee et al. (2003) and (Calder & Aitken, 2008), another advantage is that consumers' voices are free to illustrate the personal constructs that underpin their meaning systems. Finally, given the difficulties that people can face in expressing their thoughts and feelings under a relational point of view when the other part in the relationship is a SO, the use of visual metaphorical images can make people more comfortable expressing themselves and their deep emotions than they are with the use of words alone.

Data Analysis

The researchers used the qualitative analysis program NVivo 12 to assist with coding. Verbatim interview transcripts were coded in three phases, using the open-coding technique of the grounded theory (Corbin & Strauss, 1990). Images played a supporting role helping researchers delve into respondents' words. Firstly, we analyzed the responses of each informant at a level of analysis as close as possible to the way they were voiced by everyone. Then, we ran a second round of coding in which, bearing in mind the categories that emerged from the individual-level analysis, we conducted a cross-analysis among all the informants. This second phase aimed at identifying broader categories, resulting from the collapse and the merger of the previous ones, and overarching themes. Concerning these themes, an aspect deserves to be highlighted: One theme clearly emerged overall from all of the interviews, as a baseline condition in the introduction of other different themes. This common trait refers to an uncertainty component, which characterizes the relationship anticipated by the informant. The other themes, instead, emerged as different threats that informants perceived when they think about their potential relationship with the SO. Finally, in the third round of coding, we moved to an even higher level of abstraction, in respect to the uncertainty and threat level. The combined analysis of uncertainty and threats resulted in the identification of four main macro themes. Each theme corresponded to a specific fear anticipated by the respondent when encouraged to think of a future possible relationship with a SO.

Findings

Due to human-like characteristics and to intimacy, the relationship that involves a user and a SO is similar to an interpersonal one. Therefore, acquiring a SO can be seen as the start of a relationship.

From the coding, uncertainty and different kinds of anticipated threats emerged. While uncertainty emerges as a common trait across all the interviews, the four threats that emerged differ substantially from one another. Indeed, each threat presents specific features that clearly result from respondents' narratives. Main threats, their features, and the respective and most representative respondents' quotes are reported in Table 1. Codifying respondents' verbatim, a correspondence emerged between the features of each threat and the negative aspects and risks that people encounter when engaging and experiencing a negative interpersonal relationship. For example, the features of information asymmetry present some similarities with some aspects of the stalking relationship. Specifically, Being with an Always Present and Spying Partner and Being with a Surveilling Partner are similar to the feeling of being spied on experienced by people who are victims of stalking behaviors (Korkodeilou, 2017; Spitzberg, 2002). Moreover, Vulnerability to Unfortunate Events corresponds in a way to the restriction of freedom in everyday life and negative emotions experienced by the victims of stalking behaviors (Korkodeilou, 2017; Spitzberg, 2002; Spitzberg & Cupach, 2007). Similarly, Being with a Mysterious Partner recalls the presence of an unknown and anonymous partner and can characterize a stalking relationship (Parsons-Pollard & Moriarty, 2009). In this line, we defined the labels for all the other threat features reported in Table 1. Similarities between threat features and aspects of negative interpersonal relationships are reported at the end of the paragraph illustrating the findings.

The combination of uncertainty and threat, both elements that we observed in our data, can elicit fear (Frijda, Kuipers, & Schure, 1989; Keltner, 2019; Nezlek, Vansteelandt, Van Mechelen, & Kuppens, 2008; Roseman, 1996; Roseman, Spindel, & Jose, 1990; Smith & Ellsworth, 1985) and eventually inhibit the start of a relationship. In particular, we identify four types of fear: Fear of Being Controlled, Fear of Being Dominated, Fear of Being Subordinated, and Fear of Losing Self-Control. As these fears embed aspects that are typical of interpersonal relationships (i.e., the ones represented by the main threats' features), it follows that the SO acquires a social role that usually is played by people in a negative relationship: the negative partner. Therefore, we identified four SO social roles, one for each fear: Stalker, Captor, Master, and Seducer (see Figure 1).

To deeply report these findings, we created for each fear a persona in which narration and personal characteristics exemplify the features of each main threat and the social roles identified in this study. We also report the most representative images used as stimuli during the interviews as well as some verbatim excerpts of several respondents.

Main Threat: Being in a relationship characterized by…	Threat Features	Quote
Information Asymmetry	Being with an Always Present and Spying Partner	*"I imagine it's like living in an environment where you're always being spied on, because [the SO] knows you. It's like it would be aware of all of your habits and preferences."*
	Vulnerability to Unfortunate events	*"I can't live like this, it honestly bothers me. It bothers me alot. I should be able to be happy and comfortable to walk around and act normally. If I'm with my daughter, I should feel free to hug her without fear of someone taking a picture and twisting the moment into something questionable in order to blackmail me with an accusation of being a pedophile."*
	Being with a Surveilling Partner	*"This little instrument actually has enormous power."*
	Being with a Mysterious Partner	*"Actually, I don't know how the data thing works. I don't know all the mechanisms that are behind the process."*
Violence	Psychological Threats and Dominance	*"[With the smart crib], there is no need for you to be there, but for me this goes too far in the sense that: Why shouldn't I be there?"*
	Physical Threats	*"My nightmare is that a blackout will make me prisoner in a house."*
	Unavoidable Partner	*"It is inevitable because I realize that, today, you cannot stop the progress."*
	Helplessness	*"I don't know if I want [SO innovation and diffusion]. It will happen anyway, because you can't stop it, but it is starting to become a problem to manage."*
Annoyance	Closeness	*"PCs and telephones are externs, while the smartwatch is something that you have on and it oppresses and controls you."*
	Lack of Control	*"I wish to be less super-reachable and I would like to be the one that accesses the PC, even physically."*
	Loss of Autonomy	*"It is like we are now used to having these tools that do things for us."*
	Receiving Annoying Orders	*"To have an object tied to my wrist that alerts me to deadlines and other things bothers me a little…Since receiving 100 work emails a day is a little oppressive, the value of this object, with its pings and reminders, is negative."*
Addiction	Fascinating Partner	*"I recognize the great convenience and the appeal of the smart TV."*
	Salience of the Partner	*"Maybe we overuse them, and we are no longer used to doing things by ourselves."*
	Pathological Relationship	*"Today technology has become like smoking and alcohol."*
	Avid Relationship	*"Today we can no longer go out and have contact with other people without using these tools."*

Table 1. Qualitative excerpts organized by main threats and respective features.

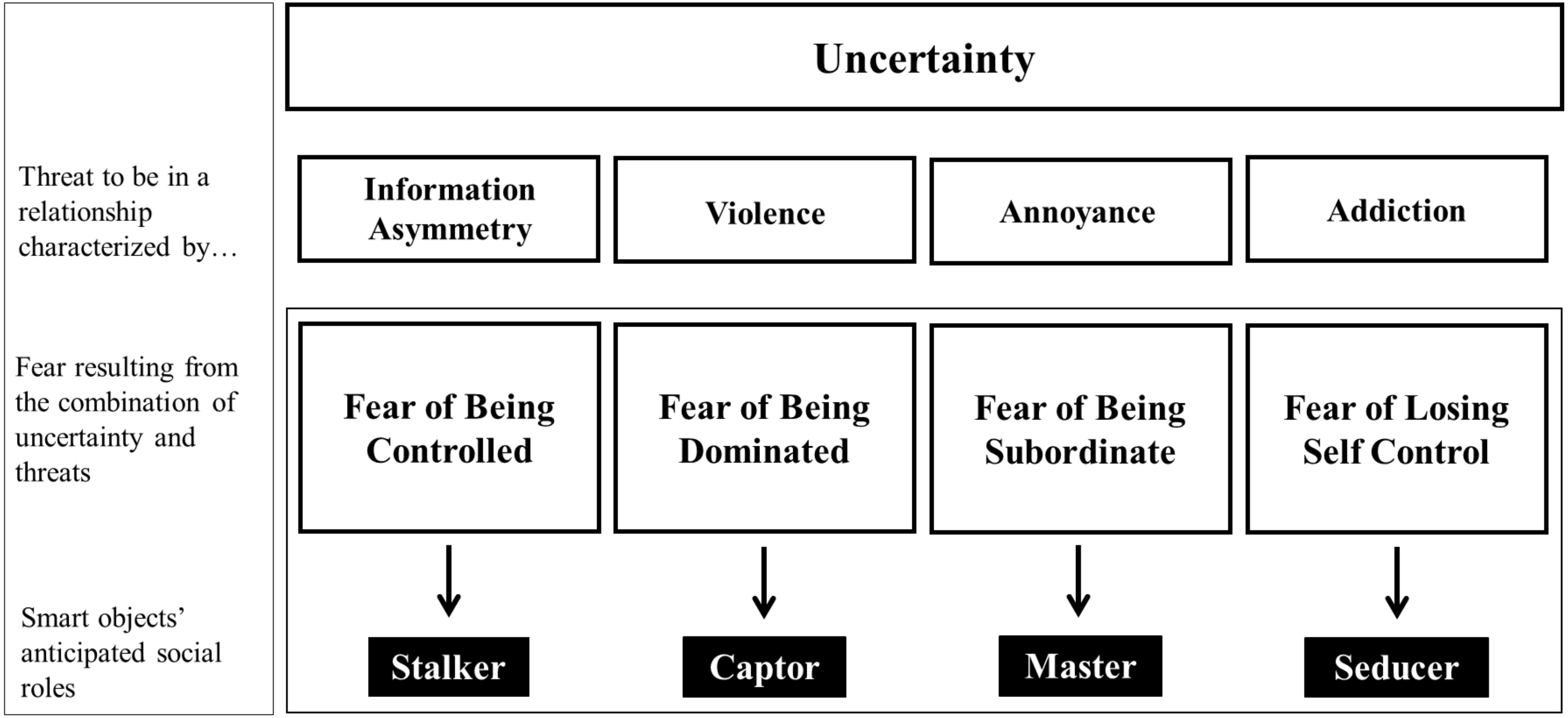

Figure 1. Resistance to enter into a relationship with a SO.

Fear of Being Controlled

Information Asymmetry as Main Threat. Fred is a 50-year-old psychologist that lives with his wife and his daughter. He considers the idea of installing a smart speaker in his house. However, he is not sure about introducing one of these SOs into his house. Figure 2 shows the images used by respondents when talking about the threat of being in a future relationship characterized by information asymmetry.

Figure 2. Fear of Being Controlled collage

Fred thinks that the relationship with the SO would expose him and his family to several threats. These objects have the capacity to take part in different aspects of the user's routines, and what worries Fred is the fact that the SO can monitor and know every aspect of his private life in all its facets: What he eats, his routines, his consumption patterns, and his habits etc. Indeed, Fred manifests his concern about the SO being an always present and spying partner (see Table 1).

"I imagine it's like living in an environment where you're always being spied on, because [the SO] knows you. It's like it would be aware of all of your habits and preferences."

Fred feels vulnerable and deprived of his privacy. He thinks that installing a SO would make him unable to hide from the device's "sight" (see eyes in Figure 2). This problem, according to Fred, makes him feeling always observed and exposes him to unfortunate events (such as hacker attacks, blackmail and being exploited for marketing purposes). Fred fears that the presence of the SO would also concretely and negatively affect his social behavior, even toward his beloved ones (see Table 1).

"I can't live like this, it honestly bothers me. It bothers me alot. I should be able to be happy and comfortable to walk around and act normally. If I'm with my daughter, I should feel free to hug her without fear of someone taking a picture and twisting the moment into something questionable in order to blackmail me with an accusation of being a pedophile."

All of these threats are facets of the main threat of being in a negative relationship with a SO, where the negative aspect is represented by information asimmetry. The combination of the main threat and the uncertainty aspect can eventually elicit the Fear of Being Controlled by the SO.

"At this moment, I don't think that technology makes me feel safer, it just makes me feel more observed."

The SO as a Stalker. In the relationship anticipated by Fred, the SO plays a role with particular characteristics. The device expresses an intrusive nature that acquires a lot of information about Fred. This creates an information asymmetry within the relationship and places the SO in a privileged and powerful position in terms of surveillance ability, as demonstrated by the authoritative figures with which he portrays the SO (i.e., a giant with a magnifying glass or Vladimir Putin, see Figure 2 and Table 1).

"This little instrument actually has enormous power."

This information asymmetry and imbalance of surveillance ability are exacerbated by the fact that the SO expresses itself in a mysterious way within the relationship. Indeed, while the SO can know a lot about Fred, there are a lot of things that Fred doesn't know about a SO. This gives the SO an aura of mystery, as is also displayed in Fred pictures (i.e., a shadow, Big Brother, see Figure 2 and Table 1).

"Actually, I don't know how the data thing works. I don't know all the mechanisms that are behind the process."

However, the power of the SO does not correspond to a coercive nature. The device, indeed, doesn't seems to directly attack the user, but his surveilling behavior makes its mere presence a danger to Fred who, therefore, sees the SO as an intimidating entity.

The threats that Fred anticipates in his relationship with the device are similar to the ones that characterize a stalking relationship: Surveillance and privacy issues (Spitzberg, 2002), home safety risks (Spitzberg, 2002), but also the presence of an unknown and anonymous perpetrator (Parsons-Pollard & Moriarty, 2009), the perpetrator's constant presence and Fred's lack of control, a limitation in terms of freedom or social life (Korkodeilou, 2017), and anxiety, suspicion, or paranoia (Spitzberg, 2002; Spitzberg & Cupach, 2007), are all threats that are present both in Fred's narrative and in stalking relationships. From this correspondence emerges the fact that the SO, in Fred's anticipated relationship, plays the social role of the Stalker.

Fear of Being Dominated

Violence as Main Threat. Rachel is 30 years old. She is concerned about the impact that technology can have in her everyday life. Figure 3 shows the images used by respondents when talking about the threat of being in a future relationship characterized by violence.

Figure 3. Fear of Being Dominated collage

Rachel's concern is connected to the fact that she believes that coming in contact with a SO can expose her to several problems that deal with her personal health, from the more existential and psychological side to the physical one. As it pertains to the existential and psychological side, Rachel fears first that this process would take away her identity: For example, she doesn't like the idea of a smart crib (see Figure 3) because she thinks that the device would replace her as a mother (see Table 1).

"[With the smart crib], there is no need for you to be there, but for me this goes too far in the sense that: Why shouldn't I be there?"

Second, Rachel claims that using this kind of device can have a negative impact in terms of autonomy, involving different parts of her life.

"We are no longer able to be autonomous. In fact, it's as if we are disoriented in a world that has become more and more technological, and which will only become more so. Therefore, even our children's children will lead increasingly technological lives, with less and less independence."

This process can result in a loss of freedom that involves Rachel herself, but also her relationship with the others. Therefore, in third place, she fears that using a SO could eventually entail isolation. This isolation can be expressed in different forms, such as a lack of dialogue with others or also a lack of need to go out.

"There are internet connections in every place in the world; you can go anywhere and connect to the internet – no problem. You can be connected and you can find out so much about people through the internet, but at the same time you are alone."

Rachel's idea about isolation, however, can go further since she also perceives the physical threat of becoming prisoner in a smart home due to a blackout (see Table 1).

"My nightmare is that a blackout will make me prisoner in a house."

This last example, connected to the event of being physically constrained, shows that the idea that the SO can hurt Rachel is not only limited to an existential and psychological side. She claims, in fact, that SOs can have bad effects on her physical health: For example, she fears damage to her brain, heart, or eyes, especially due to radiation and electromagnetic waves (see Figure 3).

"Smart objects, like a Smartphone and other electronic accessories, emanate radiation and these smart objects are often close to the brain and heart: They can bring many health problems in the long run."

All these threats are facets of the main threat of being in a negative relationship with a SO, where the negative aspect is represented by violence. The combination of the main threat and the uncertainty aspect can eventually elicit the Fear of Being Dominated by the SO.

The SO as a Captor. In Rachel's narrative, the SO has different characteristics that have an important impact in the relationship that she anticipates. As the SO can directly expose Rachel to a series of threats, it is the powerful member of the relationship. This also emerges from the fact that Rachel imagines it as a big pair of hands (see Figure 3).

"Hands that crush us: They crush us down in both our life and our work. We are manipulated by these instruments."

It is important to say that the power does not refer to the single SO itself, but it seems more connected to the general process of technological development that is seen as unstoppable and ineluctable despite its bad consequences (see Table 1).

“It is inevitable because I realize that, today, you cannot stop the progress."

This process makes the SO an unavoidable partner and puts it in a position of superiority over Rachel who, on the other hand, feels helpless. Her lack of power not only involves what happens within the relationship but also in the entire environment. In a way, we can say that she does not feel in control of the situation whether the relationship begins or not (see Table 1).

“I don’t know if I want [SO innovation and diffusion]. It will happen anyway, because you can’t stop it, but it is starting to become a problem to manage.”

As the SO can hurt Rachel in different ways, especially physically, it expresses its threatening aspect. Indeed, Rachel sees a smart home in an evil and scary form (see Figure 3).

Rachel sees the SO as a dominant and violent partner in a relationship in which it has the power and is able to hurt her. The SO’s characteristics, such as being powerful (Giebels, Noelanders, & Vervaeke, 2005; Knutson, 1980), and violent (Hillman, 1981; Wesselius & DeSarno, 1983), and its effects on the user, such as helplessness (Alexander & Klein, 2009; Giebels et al., 2005; Hillman, 1981) or isolation (Giebels et al., 2005), overlap with the literature about kidnapping. Therefore, in this fear, the SO plays the role of the Captor.

Fear of Being Subordinated

Annoyance as Main Threat. Tracy is a 50-year-old manager. Although she’s interested in smartwatches, several problems about them emerged in her narrative. Figure 4 shows the images used by respondents when talking about the threat of being in a future relationship characterized by annoyance.

Figure 4. Fear of Being Subordinated collage

Many of these issues are connected to the physical closeness that Tracy perceives with the SO, being physically tied to the user. This close relationship, according to Tracy, can have several implications (see Table 1).

"PCs and telephones are externs, while the smartwatch is something that you have on and it oppresses and controls you."

First of all, Tracy fears implications in terms of lack of control over a SO's agency and autonomy, as well as feeling of being tracked (see Table 1).

"I wish to be less super-reachable and I would like to be the one that accesses the PC, even physically."

Second, she fears that by allowing the SO to help her manage things in her life, she would become lazy in some aspects of her life (see Figure 4): This can be seen as a damage to her autonomy (see Table 1).

"It is like we are now used to having these tools that do things for us."

Finally, the close aspect of the relationship involves also a third interesting threat feature: Receiving annoying orders (e.g., notifications about deadlines, tasks, and e-mails) from the SO that makes Tracy feeling *"super-reachable."* The closeness does not permit boundaries between the user and the SO, and Tracy fears that she could lose the freedom and control to decide when to be reachable, which is something that she can do with an external device, such as a PC (see Table 1).

"To have an object tied to my wrist that alerts me to deadlines and other things bothers me a little…Since receiving 100 work emails a day is a little oppressive, the value of this object, with its pings and reminders, is negative."

So, the issue is that Tracy anticipates a relationship that expresses its imbalance in different ways, from the autonomy issue to the lack of control over her freedom. These threats are all facets of the main threat of being in a negative relationship with a SO, where the negative aspect is represented by annoyance. The combination of the main threat and the uncertainty aspect can eventually elicit the Fear of Being Subordinated.

"I think that with this object I am even more controlled and enslaved."

The SO as a Master. In Tracy's narrative, the SO has important features that characterize the relationship she anticipates. First of all, as the SO is physically close (like a ball and chain, see Figure 4) and able to constantly reach Tracy, it expresses an intrusive nature. Also, the SO is not perceived as a passive entity, but it engages, thanks to its capacity to send notifications to the user, an active behavior over which Tracy does not perceive to have control and freedom to set boundaries.

These findings have an overlap with the literature that talks about the social role of the master. First of all, besides the evident imbalance and gap between the two parts of the relationship, the master and the servant live together, implying really close proximity between the two, but also the lack of temporal limits for the servant to be reached by the master (Coser, 1973). These two aspects are also present in Tracy's narrative that claims the physical proximity and the possibility to be reached by notifications. Also, just as Tracy imagines the user, the servant faces a lack of privacy and freedom (Coser, 1973). It is important to mention, however, that some aspects from the literature do not overlap with the findings. Indeed, the punishing behavior of the master (Coser, 1973) seems not to emerge in Tracy's narrative, reporting the image of an object that is more annoying than coercive. So, the role of the master is not intended in the traditional sense, but as somewhere in between the traditional master and the modern employer.

Fear of Losing Self Control

Addiction as Main Threat. Larry is a 24-year-old architecture student. He is interested in SOs. Indeed, he thinks that these kinds of devices can be really useful and have different kinds of applications. However, this positive consideration about the SO is not limited to the useful side. He finds SOs also involving and, in a way, fascinating (see Table 1).

"I recognize the great convenience and the appeal of the smart TV."

Although Larry sees some positive aspects when thinking of a SO, from his words emerges also a dark side. Figure 5 shows the images used by respondents when talking about the threat of being in a future relationship characterized by addiction.

Figure 5. Fear of Losing Self Control collage

Larry fears that the characteristics and capacities of these devices would make him use the SO too much and he would delegate too many tasks to it. In other words, Larry thinks that the fascinating side of the SO would persuade him, making him unable to manage the balance of the relationship well. Indeed, in the scenario anticipated by Larry, he transfers his power and agency to the SO that therefore becomes too salient in his life (see Table 1).

"Maybe we overuse them, and we are no longer used to doing things by ourselves."

The fascinating aspect of the SO and its high level of salience make the relationship eventually become a pathological one. Larry fears becoming too dependent on the SO. Several images represent the pathological bond and absorption that Larry imagines with the device (like a symbiosis, see Figure 5 and Table 1).

"Today technology has become like smoking and alcohol."

The threat of being in a pathological relationship with the SO, according to Larry, takes multiple forms. The main one deals with the loss of capacities and autonomy. This aspect covers a wide palette of effects, that involves more ephemeral ones, connected to the consequent laziness of the user, to more relevant ones, such as loss of mental capacities.

"These resources and comforts make us a little dependent and we lose some natural abilities that we were forced to have and develop previously. And now, instead, they are just given to us, thanks to technology. But in the absence of it, there's a risk of creating serious damage."

Also, Larry fears an isolation process. He thinks that the use of SOs would limit several aspects of his social life. He imagines that, being so absorbed with the device, he would not leave the house, or he would not pay attention to his loved ones or the surrounding world in general. What is peculiar about this threat is that, according to Larry, even when socializing processes occur, the SO is still present: The interaction happens through the SO, or can be ruined and sabotaged by it. We can say that the consumer-SO relationship is an avid one (a group of friends together looking at their phones is a good example, see Figure 5 and Table 1).

“These days, we can no longer go out and be in contact with other people without using these devices.”

These threats are all facets of the main threat of being in a negative relationship with a SO, where the negative aspect is represented by addiction. The combination of the main threat and the uncertainty aspect can eventually elicit the Fear of Losing Self Control.

“Bloody hell, it is advantageous, but the abuse [of smart objects] then leads to not knowing how to live without it.”

The SO as a Seducer. In Larry’s narrative, the SO has different kinds of characteristics. First of all, a positive side emerges that deals not only with its utility, but also with an involving and fascinating side. The SO expresses a persuasive nature to the extent that Larry can’t manage the relationship with it well and that it can become an object of dependence for him. In that way the positive characteristics of the SO mutate into the dark side of the SO. Once the persuasion process is completed, the SO expresses all of its problematic features. It is threatening and oppressive in the way it avidly takes control of Larry’s life (like it is chaining up his hands, see Figure 5).

According to Larry’s narrative, the SO shares different aspects with the role of the seducer. The attractiveness (Ryan, 1988), the process of depravation of power (Greene, 2001) and the complicity of the seduced (Greene, 2001; Hoch, 2002) are elements present in seduction literature. Lastly, the seduction is a process that can be connected with addiction (Nixon et al., 2013), elements of which have been reported several times in Larry’s narrative, such as the salience (Griffiths, 2005; Griffiths, 2000) and the bad effects in terms of performance and social relationships (Andreassen, 2015; Young, 1999).

General Discussion

In this study, four fears have been identified, each one with a corresponding social role interpreted by the SO. Here we will summarize their main characteristics. In the Fear of Being Controlled, the SO is perceived as a controlling Stalker that can observe users, exposing them to several risks (e.g. hacker attacks). In the Fear of Being Dominated, the SO is a violent Captor that can hurt the user from an existential, psychological, and physical point of view. In the Fear of Being Subordinated the SO is perceived as an annoying Master that, being close to the user, can make him/her feel "*super-reachable*" with its notifications. Lastly, in the Fear of Losing Self Control, the SO is perceived as a Seducer that can become an object of addiction for the user, and so be part of a pathological relationship with them.

Theoretical Contribution

This work contributes to the resistance literature that examines the barriers to the adoption of SOs. Ram and Sheth's (1989) framework and its adaptation into the smart service realm (Mani & Chouk, 2018) do not consider the relational aspects of these devices. Anthropomorphic characteristics can motivate the use of SOs (McLean & Osei-Frimpong, 2019), but our results show that they can also have a dark side and be part of the resistance domain, confirming the idea that with SOs the same feature can have positive, as well as negative consequences (Puntoni, Reczek, Giesler, & Botti, forthcoming). From our results, indeed, emerges that non-users perceive threats that are connected to the possible relationship with the SO. It is not all about the device itself and its characteristics, but it is also about the implication that these characteristics and functions can have into the consumer-SO relationship. For example, the fact that the SO can always be in contact with the user is something that it is present and important both in the Fear of Being Controlled and Fear of Being Subordinated. However, perception and implications are different. When the SO is perceived as a Stalker, the attention of the consumer is more on the input that the SO receives, in what the SO "sees." When the device is perceived as a master, instead, the attention is more on the output that it produces, i.e. reaches the user with deadlines and tasks. We can find another example in the Fear of Losing Self Control: The useful and involving aspects of the SO are good per se, but they have bad and addictive-like implications when they are brought into the relationship.

This research also gives a contribution to the consumer-SO literature. This contribution expresses itself in two complementary directions: 1) Focusing on non-users, we examined not the actual relationship but the anticipated one; 2) This approach about anticipated relationships permitted us to explore other kinds of SO social roles, that have not emerged in the literature so far.

The previous literature has hypothesized social roles or examined them from a user perspective (Novak & Hoffman, 2019; Schweitzer et al., 2019). Dealing, instead, with the predictions and imagination of a non-user who is reluctant to purchase a SO, allowed us to bring to light new negative relationships and, therefore, negative SO social roles (i.e., SO as stalker, seducer, or captor) that would not have been discovered if we had not adopted this approach. Moreover, the emergence of these new social roles is even more interesting as it is the result of the combination of respondents' narratives, and sociological and psychological literature about Stalker (Korkodeilou, 2017; Parsons-Pollard & Moriarty, 2009; Spitzberg, 2002; Spitzberg & Cupach, 2007), Captor (Alexander & Klein, 2009; Giebels et al., 2005; Hillman, 1981; Knutson, 1980; Wesselius & DeSarno, 1983), Master (Coser, 1973), and Seducer (Andreassen, 2015; Greene, 2001; Griffiths, 2005; Griffiths, 2000; Hoch, 2002; Nixon et al., 2013; Ryan, 1988; Young, 1999) social roles.

Managerial Implications

From a managerial point of view, this research gives several insights. Privacy is the most important issue regarding SOs. However, engineers, developers, and managers should also focus on other concerns. Even if privacy is the central element of one of the four fears expressed by the respondents, other dark sides of SOs emerged. Issues like autonomy, identity and dependence have to be taken into account. Indeed, some of these are not novel concerns regarding these devices. For example, Leung, Paolacci and Puntoni (2018) have already claimed that identity plays a role in the consumption of technology. Companies should be careful about these issues when developing communication strategies that aim at reducing consumer resistance, as some characteristics of these technologies can entail both positive and negative consumer experiences (Puntoni et al., forthcoming). For example, several companies (e.g., Google and Amazon) promote SOs as anthropomorphic entities that play social roles (e.g., servant, or mother) in their ads, but this process can backfire. Our results show that the social aspects of SOs are not always interpreted under a positive lens: The respondents don't see the devices as a nice partner, but as a threatening presence. Therefore, companies should be really careful in the way they portray their devices. In this vein, our results are also supported by the communication strategies implemented by some brands from different industries, such as Apple and Now TV. These brands in some of their commercials highlight the agency of the user instead of the anthropomorphic characteristics of the SO, communicating to users that *they* have the control over the SO and showing to them that they always have a way out from setting up of a negative relationship. Specifically, Apple's commercials "Privacy on iPhone – Simple as that" and "Apple at Work"[ii] shows a way out from relationships where the SO can be a stalker or a master, respectively. In the former commercial, Apple highlights how it is important that users' personal information belongs to the user themselves, suggesting that buying Apple can be a way out from a relationship where the iPhone could be a stalker. In the latter, Apple shows that if the users don't want to be disturbed by an intrusive Siri, they can just ask it to "turn on do not disturb," providing a way out from a possible relationship where the SO plays the role of a master. In its Italian commercials[iii], Now TV shows the users the advantage of subscribing to Now TV (i.e., they can watch anything they want whenever they want), but it also highlights users' power of switching off the TV if they don't want to watch it anymore, thereby avoiding a relationship in which the SO can be a seducer. Thus, instead of showing a product as innovative as possible based on its anthropomorphic characteristics, companies should explain the limits - as well as the advantages - of SOs, and show how the user could properly use them in order to avoid issues and difficulties by giving control and sense of agency to the user.

Limits and Future Research

This research has to deal with all the limits of explorative and qualitative research, that, however, gives insight and room for other research. First of all, this whole sample is from Italy. As said in the methodology section, the Italian sample was considered the optimal choice to understand SO resistance. However, a cross-cultural approach can be useful to examine if cultural aspects can influence the perception of these devices and lead to different roles and fears. Also, we have to consider that the technology realm is changing fast and that the devices are learning and improving themselves over time: It is possible that the social perception of SOs, both for users and non-users, can change as well as the entire technological environment. Research should renew itself over time in order to be in step with technological development. Lastly, there are several aspects that have to be examined to understand the social perception of SOs further: Can factors such the age of consumers, their personal traits, the type of device, or its brand influence the perception of the social roles and possible threats? Future research can give an answer to all of these questions.

Conclusion

This research gives evidence that the social aspects (in particular the social roles) of SOs can be an important factor in the resistance to these kinds of technologies. Non-users express their fears in the way they imagine their relationship with SOs, which is filled with several threats that involve the consumer from the psychological, existential, and physical point of view. A new body of research that studies SOs with a relational approach is growing, and we think that this is a very useful approach to understand the way people interact with these devices. At the same time, we claim that the same approach can be useful to see how people without actual experience perceive SOs. These devices are entering into our everyday life, and people can feel vulnerable. It is important, then, to understand the fears and the issues connected to this process in order to solve them and eventually overcome the barriers to consumption. The relational approach can be a useful tool to do that.

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[1] Loretta, Google Super Bowl commercial 2020, shows a man who reminisces about the love of his life with a little help from Google. The video is available at https://www.youtube.com/watch?v=6xSxXiHwMrg

[ii] These two Apple commercials are respectively available at https://www.youtube.com/watch?v=lt5wlt1JS94 and https://www.youtube.com/watch?v=G9TdA8d5aaU

[iii] Now TV commercial is available at https://www.youtube.com/watch?v=xVkIHcU-Eks