THE RISE OF INTELLIGENT TECHNOLOGIES AND SOCIAL MEDIA: IMPLICATIONS FOR HUMAN-TECHNOLOGY RELATIONSHIPS

Les technologies intelligentes et les réseaux sociaux : Implications sur les relations humain-technologie

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PREFACE

This dissertation is presented in the connected article format, preceded by an introductory chapter and a conclusion which presents overarching contributions. The empirical studies presented in this dissertation received research ethics approval from the University of Neuchâtel's Research Ethics Board.

This dissertation presents three studies that were conducted under the supervision of Prof. Valéry Bezençon. In addition, they benefited greatly from the supervision of Prof. Sascha Alavi, who has been a close collaborator in all three studies and oversaw my research visit conducted to the Ruhr University Bochum's Sales Management Department.

I was responsible for the research from conceptualization to final presentation. However, the papers making up this dissertation benefited from the inputs of various academic at several internal presentations at the University of Neuchâtel, as well as multiple local and international conferences. All three papers are products of close collaboration with Prof. Valéry Bezençon and Prof. Sascha Alavi.

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ABSTRACT

This dissertation explores the evolving dynamics of human-technology relationships, emphasizing the implications of intelligent technologies and social media. The dissertation encompasses three distinct articles. The first article critically evaluates anthropomorphism in AI, exploring its theoretical conceptualization and application across fields like computer science, robotics, psychology, and marketing. Despite the widespread use of humanlike features in technologies, a comprehensive understanding of anthropomorphism in AI is lacking. As a remedy, this piece offers a conceptual framework and recommends best practices for future exploration, particularly in marketing and consumer behavior. The second article adopts a relationship-centric lens to analyze the impacts of anthropomorphic AI assistants, such as Alexa, on consumers. Findings from surveys and field experiments reveal that while AI anthropomorphism can enrich the user experience, it can also elicit identity threats for the users, intensify data privacy concerns, and diminish overall well-being. However, this research also unveils three practical interventions to mitigate these adverse outcomes. The third article contemplates the profound societal shifts induced by social media. It underscores that platforms like these amplify individual values of achievement and conformity. This assertion is backed by an analysis of a large set of secondary data, a consumer survey, and an experiment. In essence, this dissertation seeks to illuminate the complexities of consumer-technology relationships and their implications.

Keywords: Human-technology relationships, Artificial intelligence, Social media, Anthropomorphism, Individual values.

RÉSUMÉ

Cette thèse explore les dynamiques évolutives des relations humains-technologie à travers trois articles distincts, mettant l'accent sur les implications des technologies intelligentes et des médias sociaux. Le premier article évalue de manière critique l'anthropomorphisme dans l'IA, en explorant sa conceptualisation théorique et son application dans des domaines tels que l'informatique, la robotique, la psychologie et le marketing. Malgré l'utilisation généralisée de caractéristiques humanisées dans les technologies, une compréhension globale de l'anthropomorphisme dans l'IA fait défaut. Pour pallier cela, cet article propose un cadre conceptuel et recommande les meilleures pratiques pour les recherches futures, en particulier dans le domaine du marketing et du comportement du consommateur. Le deuxième article adopte une perspective relationnelle pour analyser les impacts des assistants IA anthropomorphiques, tels qu'Alexa, sur les consommateurs. Les résultats des enquêtes et des expérimentations de terrain révèlent que si l'anthropomorphisme de l'IA peut enrichir l'expérience utilisateur, il peut également susciter des menaces à l'identité humaine, renforcer les préoccupations liées à la confidentialité des données et diminuer le bien-être. Cependant, la recherche dévoile également trois interventions pratiques pour atténuer ces effets indésirables. Le troisième article contemple les changements sociétaux induits par les réseaux sociaux. Il souligne que ces plateformes amplifient les valeurs individuelles de l'accomplissement et de la conformité. Cette affirmation est soutenue par une analyse de données secondaires, d'enquêtes consommateurs approfondies et d'expériences. De manière générale, cette thèse vise à éclairer les complexités des relations consommateur-technologie et leurs implications.

Mots-clés : Relations humain-technologie, Intelligence artificielle, Réseaux sociaux, Anthropomorphisme, Valeurs individuelles.

CONTENTS

No pain, no gain.

اَلْحَمْدُ لِلّٰهِ

CHAPTER 1: INTRODUCTION

With the widespread adoption of intelligent technologies and social media, humans' relationship with technology has undergone a significant transformation. Intelligent technologies such as artificial intelligence assistants, chatbots, and virtual agents have become omnipresent in people's lives, shaping their experiences in numerous domains, from shopping and entertainment to education and healthcare (Grewal et al. 2020). Likewise, social media has fundamentally altered the way individuals interact with each other and companies, consume information, and form opinions about the world around them (Appel et al. 2020; Kaplan and Haenlein 2010). While these technologies offer great potential to enhance human life, they also present new challenges for human-technology relationships. As such, it is essential to understand the consequences of people's interactions with these technologies, both positive and negative, to optimize their use and mitigate their potential harms.

While we already have a considerable amount of knowledge about the positive impacts of intelligent technologies and social media in people's lives, such as convenience, enhanced productivity, and social connectedness (Grieve et al. 2013; Marinova et al. 2017; Ryan et al. 2017), their potential dark sides have received far less attention. The emerging literature suggests that these technologies may have unintended negative consequences for individuals, such as disempowerment, exploitation, and alienation (Puntoni et al. 2021). However, empirical work on the potential dark sides of intelligent technologies is limited (e.g., Baccarella et al. 2018; Moqbel and Kock 2018), and extant research on social media focuses mainly on mental health effects on individual (e.g., Kim and Kim 2017, Østergaard 2017; Valdez et al. 2020). Therefore, we need to develop a more nuanced understanding of the complex interplay between humans and intelligent technologies. We approach this overarching theme of the

potential dark sides of intelligent technologies by viewing human-technology interactions essentially as a dynamic relationship that occupies a significant place in modern life.

This dissertation examines the rise of intelligent technologies and social media and their implications for human-technology relationships. The dissertation comprises three articles that explore different facets of these implications. The first article reviews the literature on anthropomorphism in artificial intelligence (AI) across several disciplinary domains, including computer science, robotics, psychology, marketing, and consumer behavior. Humanlike features are being used in a plethora of new technologies, but our understanding of the use of anthropomorphism in AI-powered intelligent technologies is limited. Based on this review, the article proposes a conceptual framework and a set of good practices to guide future research and practice in the fields of marketing and consumer behavior (Uysal et al. 2023). The second article takes a relationship perspective to examine both the beneficial and harmful effects of AI anthropomorphism in consumers' relationships with AI assistants like Alexa. This empirical article shows that AIA anthropomorphism may threaten users' identity, which disempowers them, creates data privacy concerns, and ultimately undermines their well-being, using consumer surveys and a field experiment. Moreover, the article also uncovers three empowering and easily actionable interventions that attenuate these harmful effects on consumers (Uysal et al. 2022). The third article investigates how social media might change our society at a deeper level by examining its effects on basic individual values, achievement and conformity. The article shows that social media contributes to the emergence of a societal culture that places a strong emphasis on achievement-seeking and conformity. The article further explains the mechanisms underlying this effect through a large consumer survey and an experiment.

Across three essays of this dissertation, I try to address the following important questions:

- What are the benefits and harms of using anthropomorphism in AI? (Essays 1 and 2)
- What are critical future research directions, potential pitfalls and ethical considerations for marketing research of using anthropomorphism in AI? (Essays 1 and 2)
- How do the relationships between consumers and technology impact consumers? (Essays 2 and 3)
- How can we attenuate the harmful effects that originate in human-technology relationships? (Essay 2)
- How might social media impact the individuals, and eventually, our society? (Essay 3)

Below, I report a summary of each of the three essays of this dissertation.

Summary of the essays

Essay 1: "Anthropomorphism In Artificial Intelligence: A Review Of Empirical Work Across Domains And Insights For Future Research"

Anthropomorphism in artificial intelligence (AI) has become increasingly prevalent in consumer-facing situations, such as AI assistants like Alexa and virtual agents in websites (Bohn 2019). More recently, large language models like ChatGPT show off impressive humanlike skills. From more subtle to more advanced, the humanlike features may elicit a variety effects, but they are typically used haphazardly (Blut et al. 2021). To understand the consequences for consumers and optimize firms' product development and marketing, it is essential to understand anthropomorphism in AI. However, the existing literature on this topic is fragmented across several domains, and marketing research on this topic is limited.

To address this gap, this review article conducts a comprehensive literature review and synthesis of empirical articles published until November 2021 in Financial Times Top 50 (FT50) journals and 41 additional journals across several disciplinary domains, including computer science, robotics, psychology, marketing, and consumer behavior. Based on this

synthesis, we propose a three-step guiding framework for future research and practice on AI anthropomorphism.

The proposed framework offers a parsimonious guide for marketing managers to optimally utilize anthropomorphism in AI to the benefit of both firms and consumers. Specifically, we propose a framework consisting of three layers of analysis and develop distinct recommendations for each layer: (1) the valence and properties of effects elicited by AI anthropomorphism (e.g., positive vs. negative, linear vs. non-linear), (2) the particular context and the task type carried out by the anthropomorphized AI (e.g., mechanical vs. strategic tasks, objective vs. subjective contexts), (3) the characteristics of the individuals that are exposed to anthropomorphized AI (e.g., demographics, personality features, transitory emotional states).

Overall, this review article contributes to the emerging literature on anthropomorphism in AI in several ways (Blut et al. 2021; Pfeuffer et al. 2019). First, it integrates insights from different fields of inquiry to expedite the information flow between disciplines. Second, it offers a conceptual framework to organize the outcomes of AI anthropomorphism in a tidy and concise manner. Third, it provides key directions to guide future research endeavors.

Particularly for marketing managers, this conceptual framework identifies a key take-home message: there could be great promise in employing anthropomorphism in AI wisely, but its careless use may undermine the potential of cutting-edge new AI technologies for both consumers and firms.

Essay 2: “Trojan horse or useful helper? A relationship perspective on artificial intelligence assistants with humanlike features”

Artificial intelligence assistants (AIAs) such as Alexa are prevalent in consumers’ homes (REF). Owing to their powerful artificial intelligence, consumers may perceive that AIAs have a mind of their own, that is, they anthropomorphize them. Past marketing research points to beneficial effects of AIA anthropomorphism for consumers and companies (e.g., Foehr and

Germelmann 2020; Lin et al. 2021), while potential harmful effects have not been empirically explored. In examining both beneficial and harmful effects, this paper adopts a relationship perspective. Indeed, consumers spend large amounts of time with their AIAs, potentially developing a relationship over time that builds on an exchange of benefits and (psychological) costs. A preliminary survey and user interviews, a field study and a field experiment with AIA users show that AIA anthropomorphism may threaten users' identity, which disempowers them, creates data privacy concerns and ultimately undermines their well-being. These harmful effects particularly emerge in close, long relationships. The field experiment uncovers three empowering interventions which attenuate harmful effects of AIA anthropomorphism in relationships with consumers. We present three practical ways to empower users for handling their data privacy: (1) informing consumers about the data practices of the firm, (2) informing consumers about ways to protect their data privacy and (3) encouraging consumers to take action to protect the privacy of their data.

This paper contributes to the literature on human–AI relationships by investigating the usage and interactions with AIAs through a relationship lens. While past research has primarily examined consumers' interactions with AI as isolated instances (e.g., Benlian et al., 2020), owing to the ongoing nature of interactions and an intensive exchange of benefits and costs, we suggest that a relationship perspective is essential to investigate human-AI relationships. Second, while the benefits of anthropomorphism in AI are well documented in the literature (e.g., Blut et al. 2021; Pfeuffer et al. 2019), we show that there are psychological costs experienced by the consumers in the relationship with AIAs. We thus contribute to past literature by providing a more balanced account of benefits and psychological costs of AI for consumers.

The results of this essay also has important managerial implications. Our first recommendation to managers is to employ anthropomorphism in AI prudently, because an

indiscriminate use could undermine the potential of such cutting-edge AI technologies for both consumers and firms. Second, to minimize the harmful effects of AIA anthropomorphism and maximize its benefits, managers should empower consumers regarding the protection of their personal data. We provide managers with three consumer empowerment strategies that can be easily implemented.

Essay 3: "Social media is shifting the values in our societies: An increase in achievement and conformity"

Past research explored the beneficial and harmful effects of social media on individuals (e.g., Baccarella et al. 2018; Kim and Kim 2017), but no study has investigated how social media might change our society at a deeper level. Understanding the effects of social media on basic individual values is essential because our values guide our perception, goals, attitudes and behavior (Bardi et al. 2008; Maio 2010). We suggest that social media could be an important catalyst for a shift in two basic individual values, achievement, and conformity, transforming the very fabric of our societies. We argue that these two values are fueled by the fundamental mechanics of social media. In the first study, we analyzed longitudinal data from the European Social Survey (N≅80000) and found that greater social media exposure results in an increase in values of achievement and conformity. People want to be optimally distinctive from others around them; they seek a sense of belonging and a sense of distinctiveness at the same time (Brewer 1991). We argue that social media intensifies this to an unprecedented degree and leads to an increase in people's achievement and conformity values (Schwartz 1992). In Study 2, we replicated these findings in a large consumer survey (N=1000) and further revealed that social media use increases achievement and conformity through increased anxiety and the need for approval. In a third study (N=212), we experimentally manipulated social media exposure and show that even a brief exposure to social media could activate achievement and conformity values in users. Overall, our findings suggest that social media contributes to the emergence of

a societal culture that places a strong emphasis on achievement-seeking and conformity. Combining three different methodological approaches to investigate the same question provided convincing support for the proposed hypotheses in this essay.

In conclusion, this dissertation explores the intricate dynamics of human-technology relationships in the context of intelligent technologies and social media. By exploring different facets of these interactions, it sheds light on both the positive and negative implications they hold for individuals and society. Rather than being a harbinger of doom, my research aims to foster a balanced understanding of the impact of technology on humans without discouraging innovation and technological advancements.

Through one systematic literature review and two empirical studies, this dissertation contributes to the ongoing conversation on human-technology relationships by providing valuable insights into the potential dark sides of technology (Huang and Rust 2021; Novak and Hoffman 2019; Puntoni et al. 2021). It emphasizes the need for a comprehensive and balanced perspective when considering the impact of intelligent technologies and social media in our lives. By gaining a nuanced understanding of both the benefits and harms they entail, we can harness their potential and mitigate their negative consequences as marketers, and ultimately strive towards a harmonious coexistence between humans and technology in the modern world.

Furthermore, this dissertation goes beyond individual-level impacts and aims to bring forth broader societal implications of the omnipresence of intelligent technologies and social media. It recognizes that these technologies rapidly shape every aspect of our lives and engages with a broad conceptual scope to address overarching questions. The methodological diversity employed, including consumer surveys, field experiments, randomized controlled trials, and qualitative interviews enhances the strength of the findings and provides a robust foundation for understanding the complex interplay between humans and technology.

By offering a comprehensive understanding of the potential dark sides of technology and highlighting the importance of a balanced perspective, I hope to contribute to shaping a future where technology and innovation can be harnessed responsibly. With that, I invite future researchers, practitioners, and society at large to approach human-technology relationships with a nuanced perspective, considering both the promises and pitfalls, ultimately leading to a society where technology enriches and empowers human lives while minimizing its potential harms.

Next, I develop the three aforementioned essays, and conclude the dissertation with summarizing the main findings and contributions of my work.

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CHAPTER 2

ESSAY 1:Anthropomorphism In Artificial Intelligence: A Review Of Empirical Work Across Domains And Insights For Future Research

Uysal, Alavi, Bezençon

INTRODUCTION

New technologies are transforming marketing practice and the customer experience. Customers can now interact with the companies in a myriad of ways, most recently and markedly through platforms and interfaces that are powered by Artificial Intelligence (AI). Nowadays there are AI-powered voice assistants in millions of homes (Bohn 2019). When thinking about AI, consumers seem to envisage an anthropomorphized entity and marketers have used an anthropomorphic perspective to market AI technology to people (e.g., Amazon's Alexa) (Smith 2020). Even in popular media and culture, AI is often conspicuously in anthropomorphized form (e.g., Terminator, Blade Runner). Perhaps it is because consumers do not exactly know what AI is and they construct it along the line of what they know (i.e., a human). In a way, they need to give it a face, both literally and figuratively. Instilling human-like features in artificial intelligence (AI) has always been a fascination for human beings (Haenlein and Kaplan 2019). Following this seemingly instinctual tendency, we have built a smile, a face, a body, a personality and a voice for the machines (Mende et al. 2019; Shumanov and Johnson 2021). Many anthropomorphic AI machines nowadays surround us (e.g., voice assistants, service robots, conversational chatbots, etc.), but we are far from fully understanding the complexities of human-AI interactions and consequences of using anthropomorphism in AI. Moreover, while the concept of anthropomorphism in AI has been introduced to the marketing field relatively recently, there is a larger body of literature in the fields of computer

science, robotics and psychology. In a broad search of the literature across multiple disciplines, we have identified novel insights regarding the use of anthropomorphism in AI that will be of interest to the fields of marketing and consumer behavior. The goal of this paper is to synthesize the empirical studies in the literature on the use of anthropomorphism in AI and provide a cohesive and parsimonious framework to guide future research in the marketing and consumer behavior domains.

The tendency to anthropomorphize is present very early on in life; children attribute a mind to their toys and to characters in their stories, and this tendency is certainly carried to the adulthood. Research shows that human adults readily anthropomorphize smart objects of our day, such as social robots and AI-powered agents (Chi et al. 2021; Gong 2008). By doing so, people apply the norms of human social interactions to their interactions with the AI. This fundamentally alters the behavior towards the anthropomorphized entity; examples range from trivial (e.g., saying 'I love you' to Alexa) to critical (e.g., assigning responsibility of an accident to a self-driving car) (Lopatovska and Williams 2018; Waytz et al. 2014).

Nowadays, anthropomorphism is not only widespread in the marketplace (e.g., anthropomorphized brands and products), but has also expanded to many fields such as service, hospitality and education industries. However, the relationship between anthropomorphism in AI and consumer responses is complex, and research results are divided and scattered. Anthropomorphism in AI has been studied for a long time, especially in computer science and robotics fields (e.g., Weizenbaum 1966). With increasing exposure of AI to end consumers particularly in business-to-consumer (B2C) settings, the relevance of anthropomorphism in AI has begun to expand into marketing domain, which can be observed in the emergence of recent thought-leading articles on the topic (Blut et al. 2021; Hildebrand and Bergner 2021; Lin et al. 2021) (see also Figure 1 for the progression over the years).

In this paper, first, we delineate three main shortages in the current state of the literature on anthropomorphism in AI. First, both marketers and innovators tend to be optimistic about technological advancements. Therefore, most information systems and robotics research on anthropomorphism in AI has focused on beneficial effects (e.g., perceived enjoyment, trust, satisfaction), and almost exclusively these are the findings that have been translated to the marketing domain. While the literature has plenty of examples of both positive and negative effects of anthropomorphism in AI, the results are scattered and usually do not inform each other. Most research has focused on a stimulus-response approach in isolated cases of use or exposure and did not assume a relationship perspective between AI and user (see Novak and Hoffman 2019). An integrative yet parsimonious interpretation is needed to understand the disparate effects of anthropomorphism in AI that past literature has identified.

Second, extant literature on the use of anthropomorphism in AI has been shaped by the implicit goals of the research fields. For example, most research in information systems and marketing fields has focused on the idea that anthropomorphism is a strategy to be employed by companies towards consumers, and how this strategy might exploit the acceptance, adoption and use behavior of consumers (Kwak et al. 2017; Liew et al. 2017). While this path of research has identified many insights, consumer interactions with new technologies has transformed dramatically in the last decade. Consumers can engage with technology in different ways and be more involved in the interactions with technology if they want (O'Hern and Rindfleisch 2017). A consumer-centric (rather than a firm-centric) perspective, that is, research on how consumers perceive, engage and react to the anthropomorphic stimuli they are exposed to is scarce.

Third, while a variety of effects demonstrated in the literature may provide insights to practitioners, they may be incomplete. Emerging new research identifies individual customer traits and predispositions, socio-demographics and the context of application (e.g., types of

tasks) as potential triggers of anthropomorphism (e.g., Andriella et al. 2020; Liu and Tao 2022). The consequences of anthropomorphism in AI seem to vary tremendously according to individual characteristics and the context it is utilized (Chuah et al. 2021; Kim and McGill 2011). Therefore, it is imperative for the research and practice to consider all use of anthropomorphism in AI interwoven with its surrounding context.

These shortages in the literature and the lack of a coherent framework call for a broad review of the existing literature across research fields. To address this complexity and offer a comprehensive understanding of this phenomenon, we review and synthesize the fragmented empirical research on anthropomorphism in AI in an attempt to integrate insights from different fields of inquiry, namely, computer science, robotics, psychology, marketing and consumer behavior. Our goal is to advance the conversation and information flow between fields by bringing together streams of literature to inform three main research questions:

- What are the benefits and harms of anthropomorphism in AI for both consumers and firms, as informed by extant literature across research fields?
- How might the effects of anthropomorphism in AI differ across contexts of use (e.g., shopping, education) and individual differences (e.g., personality, demographics)?
- Based on a comprehensive conceptualization of anthropomorphism in AI, what are critical future research directions, potential pitfalls and ethical considerations for marketing research?

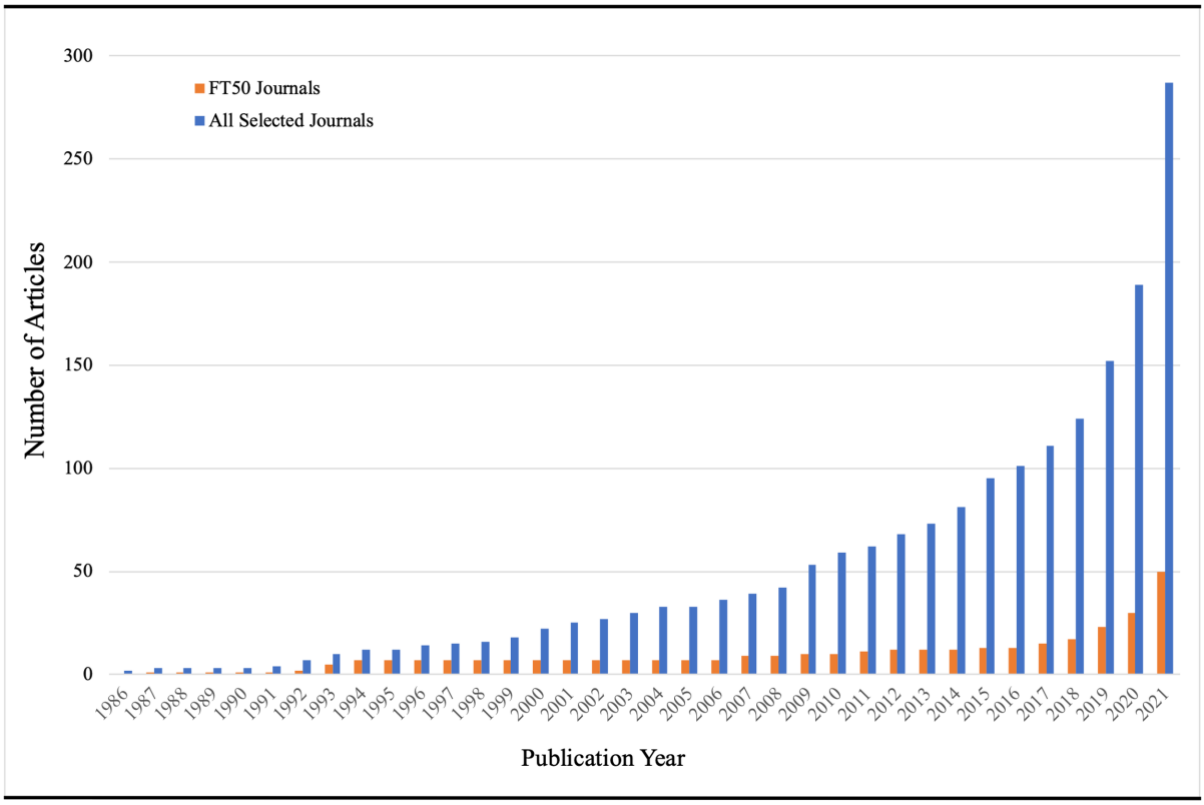
To answer these three research questions, we review and synthesize extant empirical research regarding anthropomorphism in AI and develop a conceptual framework. In our paper, first, we briefly describe and define the core concept in this research, anthropomorphism. We then review and synthesize the literature across relevant domains, pulling together the scattered research that informs the use of anthropomorphism in AI. Based on the review of the literature, we identify three overarching themes of discussion: (1) benefits and harms of AI

anthropomorphism both for consumers and firms, (2) the role of context and individual differences in the potency of AI anthropomorphism and (3) future research directions to explore, which includes a discussion of managerial and strategic implications.

ANTHROPOMORPHISM IN ARTIFICIAL INTELLIGENCE: REVIEW OF RELEVANT LITERATURE

Anthropomorphism has been commonly defined as 'the tendency to imbue the behavior of nonhuman agents with human-like characteristics' (Epley et al. 2007). These characteristics could include physical appearance, emotional and mental states and motivations. For instance, when we are faced with a nonhuman entity that possesses a human-like body or eyes, we may infer that the entity could move or see like a human. We make a behavioral inference based on

Figure 1. Cumulative distribution of articles related to anthropomorphism in AI over time.



our observation (e.g., my cat has eyes, so it must be able to see). However, when we attribute intentions, motivations and awareness to nonhuman entities, we go beyond such purely behavioral inferences and attribute a human-like mind to them (e.g., my cat is devious and

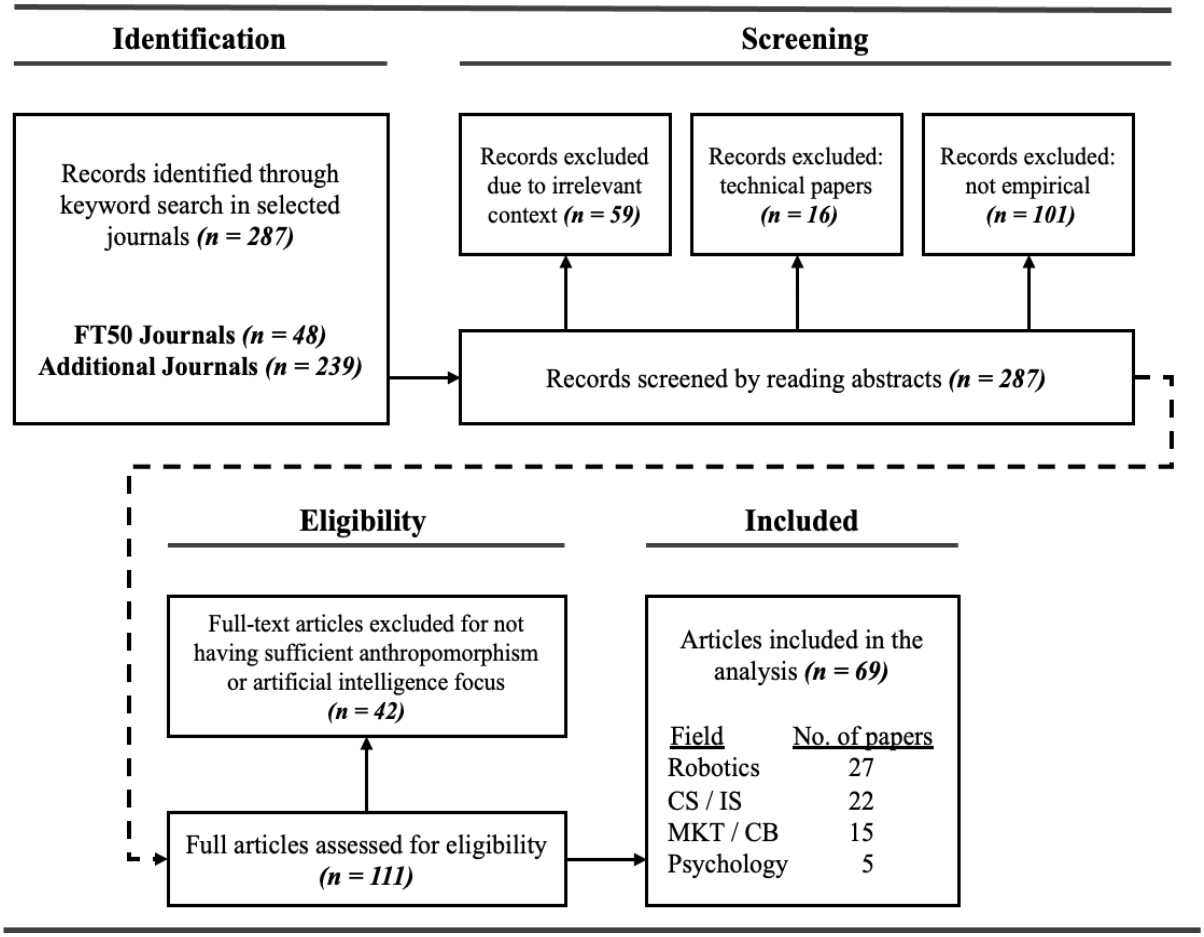
Machiavellian). A hallmark of being human is having a mental state of one's own and recognizing mental states in others different from one's own (i.e., Theory of Mind) (Premack and Woodruff 1978). Therefore, anthropomorphism is essentially about perceiving a mind in the non-human entity (Gray et al. 2007), whether it may be elicited through physical (e.g., embodiment, speech, interactivity) or mental (e.g., intentionality, emotions, cognition) human-like features (Waytz et al. 2010).

In our investigation of anthropomorphism in AI, we adopt this broad conception of anthropomorphism as a perception that AI has a mind of its own. As mentioned above, this perception could be elicited through seeing a moving, talking robot (i.e., physical features) or seeing a robot acting autonomously, seemingly with its own intentions (i.e., mental features). By adopting this definition, we aim to be inclusive of various human-like features studied in the literature that leads people to anthropomorphize, that is, perceive a mind in the AI-agent. Next, we summarize the procedures followed to conduct a comprehensive literature review for identifying and synthesizing the knowledge on AI anthropomorphism.

Literature Review Procedures

We have searched the literature for all research articles that included the following combinations of keywords: either "anthropomorphism" or "personification" that appeared together with the term "artificial intelligence" (up to November 2021). Since the earlier definitions and seminal works used the word "anthropomorphism", the term that generated most articles was the combination of "anthropomorphism" and "artificial intelligence". However, we also included "personification" as a keyword because we noticed that sometimes this term is used to denote the concept of anthropomorphism. The search terms "anthropomorphism" and "personification" were used in root form as well as full form to ensure all term-related search results were captured (e.g., "anthropomorph*").

Figure 2. Overview of review methodology.



In our topic of interest, after an initial search of the keywords, it became apparent that potentially relevant work is scattered across journals in the domains of marketing, consumer behavior, management, psychology, computer science and robotics. Since our aim is to bring together and synthesize the literature across these domains, it is useful to search the literature widely in order to capture the fragmented literature more effectively. Given the relevance of this article primarily for marketing academe and practitioners, we started our search in the FT50 (Financial Times Top 50) journals. In addition, we have complemented this with articles from relevant journals that are not included in that list. The additional journals were selected by consulting the lists and rankings provided by SCImago Journal & Country Rank (i.e., SJR Scientific Journal Rankings). To ensure the quality of included journals, we selected journals that were ranked in the top 5 in Scimago Journal Ranking (SJR) score in four sub-domains of

Computer Science (*Artificial Intelligence*, *Computer Science (miscellaneous)*, *Human-Computer Interaction* and *Information Systems*), one sub-domain of Decision Sciences (*Information Systems and Management*), three sub-domains of Business, Management and Accounting (*Management Information Systems*, *Management of Technology and Innovation*, and *Marketing*) and two sub-domains of Psychology (*Experimental and Cognitive Psychology*, and *Social Psychology*). Upon review of these ten sub-domains and removing the duplicates that were top ranked in multiple sub-domains, we identified 28 journals that might be relevant to our topic, based on the sub-domains they were listed by Scimago Journal Rankings. Finally, we included an additional 13 journals that had a focus particularly relevant to our topic (e.g., Computers in Human Behavior, International Journal of Social Robotics). Given the different levels of maturity of literatures in each particular field, we opted for a search that is as wide as possible to capture the scattered literature more effectively. This resulted in a total of 91 journals included in our literature search. Out of these 91 journals, the keyword search yielded no articles from 52 journals (57%). The full list of journals and the number of articles identified from each journal are provided in Table 1. The full list of articles included in this review is provided in Table 2.

Each journal was searched with the identified keywords and the resulting abstracts as well as full articles were reviewed for relevance. We had two main criteria for determining the relevance of the articles: First, did the article provide empirical evidence on the use of anthropomorphism in AI? Second, did the article include outcomes that could be relevant for marketing or consumer behavior fields? The second criterion, decidedly, is a more subjective one and at the initial stages we kept our range of inclusion wide. Only after going through full texts, we decided whether any insights for marketing or consumer behavior fields can be extracted. Our initial search identified 48 articles in FT50 journals, 27 articles in the journals

selected according to SJR rankings in their respective domains and 212 articles in the selected additional journals, a total of 287 articles.

Given the particular goal of our exploration to synthesize relevant literature with a marketing outlook, a high proportion of the articles were discarded for not being relevant. Specifically, after reading the abstracts, 59 articles (20%) were discarded due to irrelevant context, 16 articles (5%) were discarded due to being categorized as technical work and 101 articles (35%) were discarded due to not presenting any data (i.e., conceptual or review papers). 111 articles were included in the next round of analysis. A further 42 articles were discarded after a detailed read for not having a sufficient anthropomorphism or artificial intelligence focus (see Figure 2 for an overview of the review methodology). The final set of identified relevant articles consisted of 69 articles, with the large majority of the articles appearing in robotics (39%) and computer science (32%) journals, followed by marketing, management and consumer behavior journals (22%), followed by psychology journals (7%). However, to have a more accurate picture of the entire search, it is important to note that most of the discarded articles were from computer science and robotics journals. Figure 1 depicts the growth of cumulative mentions in the literature over the years and compares this with the mentions in FT50 articles. This variation shows that, even after discarding the context-irrelevant articles that might not inform marketing field, there is still quite a lot of information that marketing field can extract

Table 1. Journals included in the literature search.

Journal Name	# identified (# included)	Journal Name	# identified (# included)
International Journal of Social Robotics	113 (24)	Academy of Management Annals	1 (0)
Minds and Machines	45 (0)	Academy of Management Journal*	1 (1)
Computers in Human Behavior	34 (16)	Annual Review of Organizational Psychology and Organizational Behavior	1 (0)
Journal of Consumer Research*	11 (2)	Contemporary Accounting Research*	1 (1)
Journal of the Academy of Marketing Science*	11 (1)	European Journal of Operational Research	1 (0)
Journal of Service Research	8 (3)	Frontiers in Psychology	1 (1)
Journal of Marketing*	7 (2)	Human-centric computing and information sciences	1 (1)
Frontiers in Robotics and AI	5 (3)	Human Resource Management*	1 (1)
International Journal of Information Management	5 (4)	IEEE Transactions on Pattern Analysis and Machine Intelligence	1 (0)
Organization Studies*	4 (0)	Information and Organization	1 (0)
International Journal of Research in Marketing	3 (0)	Information Systems Research*	1 (1)
Journal of Consumer Psychology*	3 (0)	Journal of Consumer Marketing	1 (1)
Psychology and Marketing	3 (3)	Journal of Marketing Research*	1 (1)
Science Robotics	3 (0)	Journal of Personality and Social Psychology	1 (0)
Trends in Cognitive Sciences	3 (0)	Journal of Retailing	1 (0)
Artificial Intelligence	2 (0)	Marketing Science*	1 (0)
IEEE Transactions on Systems, Man, and Cybernetics: Systems	2 (0)	Nature Machine Intelligence	1 (0)
Journal of Business Ethics*	2 (0)	Organization Science*	1 (0)
Journal of Experimental Psychology: General	2 (1)	The Accounting Review*	1 (1)
Journal of Management Information Systems*	2 (1)	TOTAL	287 (69)

* FT50 Journals. Note: The keyword search yielded no articles from the following FT50 journals: Academy of Management Review, Accounting, Organisations and Society, Administrative Science Quarterly, American Economic Review, Econometrica, Entrepreneurship Theory and Practice, Harvard Business Review, Human Relations, Journal of Accounting and Economics, Journal of Accounting Research, Journal of Applied Psychology, Journal of Business Venturing, Journal of Finance, Journal of Financial and Quantitative Analysis, Journal of Financial Economics, Journal of International Business Studies, Journal of Management, Journal of Management Studies, Journal of Operations Management, Journal of Political Economy, Management Science, Manufacturing & Service Operations Management, MIS Quarterly, Operations Research, Organizational Behavior and Human Decision Processes, Production and Operations Management, Quarterly Journal of Economics, Research Policy, Review of Economic Studies, Review of Finance, Review of Financial Studies, Sloan Management Review, Strategic Entrepreneurship Journal.

from the neighboring fields. To increase the information flow and establish a strong link between marketing and the neighboring fields in our topic, we discuss the emerging insights from synthesizing this literature next.

Insights Emerging from the Literature

First of all, the distribution of relevant articles over time shows that the anthropomorphism phenomenon in AI has recently been introduced to the fields of marketing, consumer behavior and management. Especially the last three years (2019-2021) has seen a significant increase in the interest of these field to the topic at hand (Figure 1). The increased mention of this topic in FT50 journals captures how seriously and eagerly it is adopted by the marketing and consumer behavior domains as well as its potential in the upcoming years. Despite a larger number of articles overall appearing in computer science and robotics journals, the cumulative distribution of relevant articles over time parallels the increased attention AI anthropomorphism is getting in FT50 journals. A steady growth has been present in the literature roughly since a decade, and the last three years in FT50 journals follow that growing trend.

In our examination of the selected articles for general themes, it became quickly apparent that different research domains have different overarching goals. Majority of articles from robotics are more concerned with better utilization of anthropomorphism in AI, articles from computer science attempt to experiment in a wide variety of contexts ranging from medical to educational use of anthropomorphism in AI and the articles from marketing and consumer behavior fields largely focus on outcomes for firms. Moreover, there is another conspicuous divide in the literature in relation to positive and negative effects of anthropomorphism in AI. 36 out of 69 articles (52%) reported only positive or negative effects. One of the problems we observed with this group of articles is that their positive or negative effects, in isolation, do not seem to inform any other contexts than their own. While there is no consensus on the prevalence of positive or negative effects, more importantly, approximately

half of the articles we reviewed have a single outlook. They do not consider both potential positive and negative effects in the same framework, and the contingencies or the potential individual differences. On the other hand, 33 out of 69 articles (48%) reported positive or negative results that depended on the particular context of use, or the characteristics of the individuals including age, gender and personality.

In summary, across the domains of literature we examined for relevant works, we see an increasing trend for the interest in anthropomorphism and AI. However, the research outlook and questions addressed across different domains cover a wide range. Based on our examination of the emerging themes in the literature, we identified three themes of interest that allow us to draw distinctions between different contingency conditions. The three themes can be summarized as: positive versus negative effects, the particular context of use for anthropomorphism and AI, individual differences in the perception and efficacy of anthropomorphism in AI. It is important to note that these three groups of examination, in a way, build on each other. There is sufficient evidence to show that (1) anthropomorphism in AI has ambivalent effects, which (2) depend on the context in which it is utilized, which (3) further depend on the individual characteristics of the user. Our reading of this disintegrated literature provides the basis for the conceptual framework of anthropomorphism in AI, which we develop and discuss in line with the three thematic foci we identified.

ANTHROPOMORPHISM IN AI: CONCEPTUAL FRAMEWORK

We can summarize this literature review into a coherent whole by aggregating the three distinguishing perspectives. We begin with a comparison of positive and negative discrete effects of anthropomorphism in AI, followed by the role of contextual factors which brings the first level of granularity to our investigation and finally we end with the role of individual user differences which allow us to arrive at a distinct, refined conceptualization of anthropomorphism in AI. Figure 3 summarizes the progression of our framework in three steps.

Our goal in proposing this framework is to highlight the dimensions of anthropomorphism in AI that need to be considered for its optimal use to the benefit of both consumers and firms. Following this layout of examination could be a benefit both for researchers and practitioners in future research designs as well as for applications of anthropomorphism in AI. This conceptual framework, built by the synthesis of relevant literature across research fields, will inform the marketing and consumer behavior domains with findings and insights accumulated in other research domains over a longer period of time.

Anthropomorphism in AI: Beneficial and Harmful Effects

The use of anthropomorphism is widespread and decades of research have attempted to uncover its effects when used in robots, computers, chatbots, virtual agents and even brands (Breazeal 2003; Kim and Sundar 2012; Weizenbaum 1966). While relevant research goes back at least half a century, the fascination with endowing machines with anthropomorphic features expanded around the turn of the century and has grown immensely ever since (Figure 1). Although there is little consensus about the elicited effects, the literature broadly divides into two, the larger of the two representing beneficial effects, and a relatively smaller stream of research representing harmful effects. While the former stream argues the positive effects of anthropomorphism in AI mostly based on anthropomorphism theory (e.g., Epley et al. 2007), the latter stream of literature argues for negative effects of anthropomorphism mostly based on uncanny valley or expectation confirmation theory (Mori et al. 2012; Oliver 1980).

A prominent argument in past literature is that anthropomorphism facilitates human-machine interactions by creating familiarity, enabling the human users to understand and predict the behavior of the machine (Epley et al. 2007; Epley et al. 2008). A large body of literature has sprung from this core proposal and anthropomorphism has been shown to foster trust (Foehr and Germelmann 2020), trust resilience (de Visser et al. 2016) and psychological closeness (Eyssel et al. 2012) towards robots and various AI agents, increase their perceived

competence (Waytz et al. 2014) and social presence (Etemad-Sajadi et al. 2021), enhance the enjoyment (Konijn et al. 2021; Qiu and Benbasat 2009), usage intentions (Hu et al. 2021) and satisfaction of the customer (Rhim et al. 2022). By increasing the perception of similarity and perhaps bridging the human-machine gap, instilling human-like features in machines have been used as a strategy to facilitate human-machine interactions (Li and Sung 2021; Pitardi and Marriott 2021).

On the other hand, several theories have argued that anthropomorphism is not unequivocally beneficial. When the perceived similarity increases, this may mean that the human-machine gap is bridged, but also that the human-machine distinctions are blurred. The uncanny valley theory suggests that increased human likeness in a non-human entity leads to increased affiliation to the entity up to a certain threshold (Mori et al. 2012). When this threshold is reached, the affinity plummets dramatically *into the valley*, before increasing again when closer to perfect human likeness (see Thepsoonthorn et al. 2021 for experimental evidence supporting this proposition). This occurs when the entity is highly human-like, but still distinguishable from a human, eliciting a feeling of eeriness and discomfort. Although proposed theoretically, no non-human entity has been able to reach a level of human likeness that results in great levels of affinity, and such hypothetical entities has only been depicted in popular culture (e.g., Philip K. Dick's replicants, Westworld's hosts). Another theory suggesting that anthropomorphism could create ambiguous effects is the expectation-confirmation theory. Nowak and Biocca (2003) argues that more anthropomorphic images set up higher expectations for the interaction partners, which create a disadvantage if the expectations are not met. In our examination of the literature on anthropomorphism in AI, we see plenty of research in similar veins.

Earlier research (2000s) showed that people give social responses to computers with anthropomorphic interfaces. Higher human likeness in computers lead respondents to rate their

computer partners more positively, perceive more competence in them and actually had higher reported trust towards the computers (Burgoon et al. 2000; Gong 2008). Similar outcomes have been tested and revealed in many other technological inventions. While providing a humanoid embodiment and a human voice in chatbots elicited a strong social presence and higher trust in humans (Qiu and Benbasat 2009; Rhim et al. 2022), a further look into this effect showed that even subtler cues can succeed in eliciting the similar effects. Simply giving a human name to a virtual conversational agent was sufficient to increase the perception of the agent as being human-like (Araujo 2008).

While this line of research has started with computers and relatively simple robots, recent research has tested much more capable and smarter variants of AI-powered machines. Artificial Intelligence Assistants (AIAs) such as Alexa are prevalent in consumers' homes and recent research shows that anthropomorphism, so to speak, bridges the human-machine gap. When AIAs are perceived to be more human-like, they are regarded as more trustworthy and evaluated more positively overall (Li and Sung 2021; Pitardi and Marriot 2021). When used in a sales context, anthropomorphism was useful in eliciting consumers' trust in relation to the sales recommendations, in a way being perceived as an entity of its own, detached from its manufacturer company (Whang and Im 2020). In other words, people liked it when the recommendations came from Alexa, but not from Amazon. These results point at the potential of using anthropomorphic AIAs to form stronger consumer relationships with the brand.

Recently, however, anthropomorphism has received the most attention in the service industry. Many service robots have found a place for them in the service journey, being utilized increasingly frequently in the closest proximity to consumers. The attitude of the researchers towards anthropomorphism in service agents and robots has been so far overwhelmingly positive. Multiple studies have asserted that anthropomorphism is a critical feature for social agents and robots that are used in the service frontlines involving social interactions (Chi et al.

2021; Delgosha et al. 2020; Zörner et al. 2021). Similar to the results found in chatbots and computers earlier, higher anthropomorphism in humanoid service robots influenced the perceived trustworthiness positively (Christoforakos et al. 2021; Zörner et al. 2021). In some cases, the effect of anthropomorphism on perceived trust and competence was found to be indirect, through perceived animacy, empathy and interactivity of the AI-powered machines (Bartneck et al. 2009b; Pelau et al. 2021). Indeed, when the robots displayed more natural-looking movements or made appropriate eye contact with the interaction partner, they were perceived more sociable and the quality of the human-robot interaction was rated higher (Kompatsiari et al. 2019; Schillaci et al. 2013). The literature provides plenty of evidence for a positive perception of machines when anthropomorphized.

On the other side of the coin, there is also emerging evidence about negative effects of anthropomorphism in AI. Particularly in humanoid service robots (HSR), research has shown that when the robots are highly anthropomorphic, human interaction partners may rate the robots more negatively, feel greater discomfort and technophobia (Huang et al. 2021; Mende et al. 2019; Sinha et al. 2020). The anthropomorphic appearance of the HSRs lead to a feeling of threat to human identity in the interaction partners, which may be explained by the need to uphold a perception of human distinctiveness (Ferrari et al. 2016; Müller et al. 2021). The same effect was observed in virtual avatars where an online experiment confirmed that highly anthropomorphic virtual avatars elicited a greater feeling of eeriness compared to simpler, cartoonish, less anthropomorphic avatars (Shin et al. 2019). However, there were also studies who took a critical stance against this stream of findings relying on uncanny valley theory and showed no effects of discomfort in highly anthropomorphic androids (e.g., Bartneck et al. 2009a). Another study reported that higher levels of anthropomorphism increased people's perception of the effort required to use anthropomorphic AI devices (Gursoy et al. 2019), which contradicts the beneficial effects found in the literature (Chi et al. 2020).

An account of beneficial and harmful effects of anthropomorphism in various AI-powered machines certainly carries some guidance for future research. However, these two streams of literature (i.e., beneficial vs. harmful effects) seem disconnected from each other, that is, they deal with different constructs and do not inform one another with their findings. From this section of the literature, one can only infer that there are certain benefits and certain harms of employing anthropomorphism in AI. The findings that show discrete effects, taken without their whole context, are not exceptionally helpful to practitioners. We expand on this issue in the next section.

The Role of Context: Conditions that Impact the Potency of Anthropomorphism in AI

A promising step we observed in the development of the literature on anthropomorphism in AI is the trend in research from investigating discrete effects towards considering the context in which the effects occur. The articles that we review in this section suggest that researchers should clearly delineate the context in which they want to employ anthropomorphism and the effects they want to elicit. Our analysis shows that handling anthropomorphism is a delicate matter. When used appropriately, it can be very advantageous to the wielder in eliciting the desired effects. A second insight that arises from this section is that anthropomorphism in AI should be used in a context-specific way, rather *narrowly*, to elicit a particular effect in a particular context. For example, a study found that people perceived human-like robots and tablet computers essentially the same, showing no effects of anthropomorphism (Leichtmann and Nitsch 2021). While this could indeed be a confirmation of a null hypothesis, it is also a good example of trying to elicit effects in very isolated scenarios. The particular robots used and the particular scenarios that the participants were tested all have impact on the perception of humanness in a non-human entity. Every other study seems to design and test their own idiosyncratic human-like robots, and the outcomes may not be entirely comparable. Even when studies sometimes test the same constructs, their operationalization differs greatly. Therefore,

it is necessary to pay close attention to the context in which the studies were carried out, including the minute details of the experimental procedures. Next, we present a detailed review of findings that attest to the crucial role of context.

Recent research shows that humanoid service robots are better able to recover from service failures thanks to their anthropomorphic nature (Choi et al. 2021). To err is human, as the saying goes, and assigning humanness to a robot, in a way, *excuses* the robot for making a mistake. However, a contrasting perspective is the matter of responsibility. Consumers penalize brands less when an algorithm (rather than a human) causes an error that harms the brand (Höddinghaus et al. 2021; Leo and Huh 2020). Moreover, the perceived harm caused by the algorithm is higher when the algorithm is anthropomorphized (vs. not) (Srinivasan and Sarial-Abi 2021). In this case, consumers seem to perceive that algorithms are objective and deserve less penalty for their errors, but any human likeness brings out the tendency to assign responsibility to the entity. Discovering a human element in a non-human entity, therefore, could elicit a wide range of reactions based on the context (Shank et al. 2019). Another proposition is that people attribute a mind to the AI-agents in a self-serving way, depending on the interaction context and the outcome. In a cooperation task with human-AI teams, people who lost as a team ascribed greater levels of mind to the anthropomorphic AI agent compared to those who won as a team. In such a context, people easily abdicated the responsibility of losing and attributed the responsibility to the perceived humanness of the AI-agent, but were more reluctant to give credit for the success (Lefkeli et al. 2021).

A popular use of anthropomorphism in AI is to elicit more disclosure from the human interaction partners. Pickard and Roster (2020) found that people disclosed more, especially sensitive information, to anthropomorphized conversational agents, compared to a human interviewer. This finding hints at a social desirability bias (Zerbe and Paulhus 1987), where people felt more comfortable sharing sensitive information when the agent was, in fact, *less*

human, since the comparison is to a human interviewer. This finding points to a potential utilization of anthropomorphic AI-agents in the medical context where, for example, patients may disclose sensitive, perhaps embarrassing information more truthfully to an AI-agent compared to a human doctor or nurse. However, this study lacked a comparison with non-anthropomorphized agents. In another study, findings show that when it is desirable to detect if people are lying, the pursuit of a greater human likeness could be counter-productive (Schuetzler et al. 2019). Therefore, even less human likeness could yield the best result in this context, that is, a machine-like AI-agent could elicit the most honest disclosure from people.

The research on human versus algorithm evaluation mechanisms in an interview setting identifies a contrasting perspective about self-disclosure. In an interview setting, although people thought dehumanizing (opposite of anthropomorphizing) the algorithm allowed to get rid of human biases, they still preferred the "devil they know" (Mirowska and Mesnet 2021). Since they did not have a readily available behavioral framework to engage with an algorithm, they preferred the anthropomorphized algorithm, benefiting from anthropomorphism as an uncertainty reducing mechanism. Reinjecting a semblance of a social relationship into the situation allowed the participants to rely on their existing behavioral frameworks. This is an example of a situation where the marketing managers should decide what effect they want to elicit. If reducing the perception of a human bias is to be prioritized, then imbuing the AI-agent with human-like features could be disadvantageous. If, on the other hand, the managers prefer to achieve the best evaluated AI interviewer, then perhaps anthropomorphism could help achieve that. In a related study with chatbots, it was shown that anthropomorphism was beneficial for transaction outcomes (e.g., conversion rate), but lead to an increase in offer elasticity (Schanke et al. 2021). As the chatbot became more human-like, consumers shifted to a fairness evaluation or a negotiating mindset. Consumers seem to think that they cannot negotiate with a purely artificial mind. However, when they perceive humanness in the entity,

in a way, they switch to the framework of human behavior and believe that they can talk a human-like agent into a desired outcome. Again, the particular effect that marketing managers want to elicit is key and high anthropomorphism will not be necessarily advantageous in all situations.

We find further granularity in relation to the context of using anthropomorphism in AI in the following studies that investigated the role of type of tasks that are carried out by the AI agents. People seem to attribute certain tasks more easily to AI, that is, computational, objective and usually prosaic tasks (Castelo et al. 2019). When AI is used outside the sphere of such presuppositions, apparently, an incongruence occurs. Research has found that higher anthropomorphism afforded greater trust to the robo-advisors, as well as a greater recommendation acceptance (Hildebrand and Bergner 2021). On the other hand, although people perceived a greater familiarity towards the anthropomorphic robot, they evaluated the more machine-like (i.e., less anthropomorphic) robot more positively, exhibited greater purchase intention and willingness to pay (Kwak et al. 2017). It seems like anthropomorphism impacts the agent in each task differently. It could be that machines are stereotypically seen as executers and not planners. In such tasks that require efficiency and objectivity (e.g., execution of a purchase), a machine-like AI could be preferred, while in tasks that require subjectivity and strategy (e.g., planning and recommending a purchase), a more human-like AI could be perceived to be a better fit for the task (cf. Castelo et al. 2019). The congruence of the task type and the agent is so pervasive that even specific anthropomorphic features create a difference in their effect. A study showed that a robot that manifests a gender (male vs. female) and personality (introvert vs. extravert) that conforms to its occupational role stereotypes (introverted male in a security role vs. extraverted female in a healthcare role) were evaluated most positively in all combinations (Tay et al. 2014). Moreover, a study with frontline service robots shows that the perception of the robot changes according to whether the robot is

augmenting or substituting the human in its task (McLeay et al. 2021). Interestingly, people did not like when an anthropomorphic robot replaced a human in a task, compared to a non-humanoid self-service machine. After all, AI agents intend to mimic some aspects of humanness and it seems that creating a collection of human features that is congruent with the context may be crucial in gaining consumer satisfaction (Karimova and Goby 2020). In certain tasks (e.g., medical decisions), people may have stronger biases against anthropomorphism in AI (Fraune 2020; Yun et al. 2021). These findings highlight the delicate nature of employing anthropomorphism in AI-powered machines in various contexts.

In our examination of the literature, a good example of a context-appropriate use of anthropomorphism in AI caught our attention in the domain of e-learning. The following studies used anthropomorphism in AI-agents in education settings successfully and converge on the beneficial effects. Endowing a robot with non-verbal cues (e.g., eye contact, gestures) in human-robot interaction were beneficial in message retention and contributed to the positive perception of a social robot (Striepe et al. 2021; van Dijk et al. 2013). The careful integration of many anthropomorphic features could therefore result in positive learning outcomes. Indeed, Konijn and colleagues (2021) showed increased learning gains over time when training with a social robot, compared to a tablet. However, they argue that this is not a direct effect, but mediated by perceived enjoyment of the learning activity. Another study found that an anthropomorphic robot presence elicited beneficial effects on Stroop test performance, only when the participants interacted with the robot (Spatola et al. 2019). The effect was, similarly, not directly on learning outcomes but rather was mediated by increased attentional control in participants due to the social nature of this interaction. In these distinct education settings, the studies were able to elicit positive effects for learning outcomes. Of course, the lack of contrasting evidence in the literature to date does not confirm the lack of effects. Future research should investigate the use of anthropomorphism in AI in this particular context in

detail, explore further benefits and potential drawbacks. With that said, we think that this is a context which might be particularly suitable for employing anthropomorphism in AI-agents. The interactions with the AI-agent is confined, in a positive sense, to a particular context and this could be the necessary circumstance to elicit desired effects and avoid undesired ones.

After reviewing the illustrations of anthropomorphism in AI in numerous contexts, we suggest that anthropomorphism in AI could be a great facilitator in human-AI interactions, but also a hindrance if used haphazardly. Therefore, managers should precisely delineate the context in which they want to employ anthropomorphism in their AI-powered machines optimally.

Individual Characteristics of AI Users

At this point in our discussion, we go one step further in the level of granularity of our examination of the literature. After reviewing the positive/negative effects and the importance of context, we now turn to the third theme of focus that we identified in our review, the role of individual characteristics. Relevant studies in the past have reported demographics as control variables and sometimes showed significant effects of age and gender on the perception of anthropomorphism (e.g., Stanton and Stevens 2017). However, there has been an expansion in research to investigate the individual characteristics themselves, mostly in the last five years, which we review next.

Research has shown that age is a critical factor in the individuals' tendency to anthropomorphize robots (Jacobs et al. 2021). For instance, anthropomorphism improved people's perception of trust in smart healthcare services and was particularly effective for younger adults (Liu and Tao 2022). These findings might suggest a generational shift towards greater acceptance of robots, but it is not a clear-cut conclusion. Another study showed that older users perceived higher interactivity and trust in the socially oriented (i.e., higher anthropomorphism) digital assistant only when they were high in internet competence, while

for users low in internet competence, a less anthropomorphic digital assistant lead to better outcomes (Chattaraman et al. 2019). The new generation of consumers are not just tech savvy, but are natives of technology. Therefore, more research on generational marketing of AI technologies is needed to unveil further effects of age.

Gender differences might also play a role in perception of anthropomorphism. While anthropomorphism in AI-agent resulted in more positive outcomes for females in a medical setting (Liu and Tao 2022), an opposite effect was found in a sales context (Liew et al. 2017). The social presence of an anthropomorphic avatar improved the website trust and patronage intentions among male participants, however, it led to lower information credibility and patronage intentions in females. This study argues that females were more critical towards the shortcomings of the avatar, particularly limited interactivity and low quality of dialogue (Liew et al. 2017). Another study found similar gender effects, showing that females were less likely to trust a robot which stared at them (Stanton and Stevens 2017). The contrasting results could be due to different methods, as the participants in the former study (Liu and Tao 2022) did not interact with the AI-powered agents, but rather read a description about them and provided ratings, while in both of the latter studies the participants actively engaged with the AI-powered avatars. This difference suggests that the expectations regarding the human-likeness may be elicited only upon interacting with the entity. Future research should take this into account and carefully construct their experimental procedures.

Individual differences that impact the potency of anthropomorphism in AI go beyond age and gender. Kim and McGill (2011) showed that people with high social power think that they can control the outcomes from anthropomorphized entities, which decreases their risk perception. An anthropomorphized entity, in a way, is perceived to be bound by the same social norms and rules as a human, it *behaves*, as a human would. It can be bullied, tricked and convinced. However, one cannot negotiate with a machine-like entity; a machine does not

behave but *generates*, and is not swayed by the persuasive tactics we are accustomed to use. This result provides an insightful peek into the mechanisms of people's behavior. However, when the individual has low social power, the tables are turned. The individuals with low social power prefer to engage with the machine-like entity because they think they cannot control the outcomes of an anthropomorphized entity, after all, sweet-talking and cajoling others in a social situation is not their forte (cf. Uysal et al. 2020). Similarly, another study shows that the same pattern emerges in individuals with higher versus lower financial status. People with higher financial status afforded more humanness to non-human entities, and expected more favorable treatment from them; in a way, they still expected human social norms to be enacted (Kim and McGill 2018). These findings highlight the crucial role of choosing the target audience appropriately. If targeted incorrectly, anthropomorphism in AI could work in the opposite direction and lead to undesirable outcomes.

An important part of the individual characteristics is people's personality. Our personality, in a way, are the glasses through which we look and perceive the world around us (Jung 2016) and perception of anthropomorphism is no exception to this. A significant positive relationship between extraversion and the tendency to anthropomorphize the robots was found (Kaplan et al. 2019). Research has shown that extraverted people tended to prefer human-like robots over machine-like robots (Chuah et al. 2021). Moreover, the combinations of multiple personality features could result in different outcomes. When individuals are high in both extraversion and openness to experience, the outward appearance (i.e., the anthropomorphic features) of a robot mattered more than their internal quality. While introverted people tended to prefer more machine-like robots (Syrdal et al. 2006), higher openness to experience predicted more favorable responses to social robots (Allan et al. 2021; Chuah et al. 2021). In addition to personality, even transitory states of the individuals or time constraints for completing tasks could impact the efficacy of anthropomorphism in AI (Reig et al. 2021). For

instance, Crolic and colleagues (2022) showed that when the individuals interacted with the chatbots in an angry emotional state, the chatbot anthropomorphism could have a negative effect on customer satisfaction, firm evaluation and purchase intentions. This stream of research lends further support to the notion that the particular audience that anthropomorphized AI agent interacts with can make or break the success of anthropomorphism in AI.

The following studies take it a step further and show that not only the personality characteristics of the individual matter, but also that the personalities of the human and the AI in the interaction should be complementary. Tang et al. (2021) showed that human and AI should exhibit complementary (vs. similar) anthropomorphic features: in a human-AI cooperation setting, when a task requires order, if both the human and the AI exhibits conscientious characteristics, in a way, they step on each other's feet. The authors argue that a conscientious employee and a highly intelligent robot may form a suboptimal pairing. Therefore, they suggest that pairing intelligent machines (i.e., high in orderliness) with employees lower in conscientiousness to reap the optimal benefits in performance increase. However, in contrast to this finding, another study found that participants achieved better performance with a robot helper that had a similar personality to them, or a human that had a different personality (Andriella et al. 2020). In addition to the characteristics of individuals and their complementarity with the AI, the types of tasks carried out in a human-AI cooperation setting should be carefully examined since working with intelligent machines could lead to a greater role ambiguity (Tang et al. 2021).

Finally, research has unveiled cultural differences in acceptance and adoption of anthropomorphized AI (Kaplan 2004). Kamide and Arai (2017) found that Americans perceived more comfort and controllability in anthropomorphic robots, compared to Japanese respondents. Moreover, in a study across 27 countries, it was shown that a country's openness to innovations had an impact on the perception and experience of the individuals with robots

(Turja and Oksanen 2019). For example, Dutch people had a greater tendency to anthropomorphize social robots than Germans. In addition, unsurprisingly, the individual's attitude towards technology is also an important determinant in the perception of anthropomorphism in AI (Youn and Jin 2021).

In reviewing the studies in this section, we suggest that individual characteristics create yet another level of complexity in implementing anthropomorphism in AI. Even though managers are able to delineate an appropriate context, the individual characteristics of the audience that are exposed to such anthropomorphism will determine its efficacy. Any use of anthropomorphism without considering the context and the individual characteristics will be largely arbitrary. Practitioners can still elicit advantageous effects, but without meticulous forethought, those effects might be coupled with some undesirable side effects. In fact, we already see hints of this in the literature, when neutral effects are occasionally reported. This apparent neutral effect might be masking ambivalent attitudes underneath. People report many positive and negative evaluations related to anthropomorphism in AI, and rather than canceling each other and resulting in a neutral attitude, this is an indication of being torn between two attitudes (Stapels and Eyssel 2021).

Summary

We have reviewed the emerging literature on anthropomorphism in AI and propose a framework of analysis consisting of three steps that provides a guide for future research designs and practical implementations of anthropomorphism in AI (Figure 3). While the marketing literature has largely found anthropomorphism in AI as a beneficial feature, research also shows some downsides of incorporating anthropomorphism in AI. Many studies state that anthropomorphism facilitates engagement with customers, and while certainly true to an extent, such blanket statements are far from capturing the complexity of real life settings and individuals when interacting with anthropomorphic AI. Overall, the findings in the literature

are largely inconsistent to the naked eye, but a careful examination shows the complexities and nuances of employing anthropomorphism. Our review of the literature does not offer a list of dos and don'ts, but reveals a way to reconcile the inconsistent findings in the literature, summarizing the circumstances and the populations in which anthropomorphism in AI could be most effective for the firms and the consumers.

In the first layer of our analysis, we found that one literature stream relies on anthropomorphism theory (Epley et al. 2007) and suggests that anthropomorphism in AI has positive effects, while the other literature streams relies on either to uncanny valley theory or expectation confirmation theory to argue for negative effects. In the second layer of our synthesis, we attempt to resolve these inconsistent findings, clarifying under what circumstances anthropomorphism in AI could be beneficial for firms or customers. Finally, in the third layer, we explored the studies on how the effects of AI anthropomorphism might differ based on individual characteristics. Our review included a large body of empirical work that allows us to provide novel insights for future research in the marketing and consumer behavior fields (see Table 2 for a summary of the literature). Our findings show that the potency of AI anthropomorphism is contingent on contextual and individual characteristics. We suggest that this three-layer analysis is a valuable exercise in guiding managers to the most optimal implementation of anthropomorphism in AI (Figure 3).

While this framework has practical utility when implementing anthropomorphism in AI, another discussion is necessary to understand how and why its effects differ across individuals and contexts. Next, we offer a theoretical lens that might be useful to make sense of this variation. ***A Relationship Perspective to Understand The Variation in Harms and Benefits***

At the beginning of this chapter, we stated that anthropomorphism is essentially about perceiving a mind in a non-human entity. By doing so, people do not necessarily believe that

Table 2: Overview of literature on anthropomorphism in AI.

Article	Type of AI	Relevant Variables Examined	What kind of effects are reported?	Did the study investigate a contingency of a context?	Did the study focus on individual characteristics of participants?
Abubshait et al. 2021	Robots	Social attention	Positive	Types of humanlike features	None
Allan et al. 2021	Social robots	Robot anxiety, Attitude	Positive and Negative	None	Personality traits
Andriella et al. 2020	Robots	Cooperation performance	Positive and Negative	None	Personality traits
Araujo 2018	Conversational agents	Social presence	Positive	None	None
Bartneck et al. 2009b	Robots	Perceived Intelligence	Positive	None	None
Burgoon et al. 2000	Computers	User evaluation, Sociability	Positive	None	None
Chattaraman et al. 2019	Digital assistants	Interactivity, Trust	Positive and Negative	Level of internet competence	Age differences
Chi et al. 2021	Social robots	Trust, Effort Expectancy	Positive	None	None
Choi et al. 2021	Humanoid service robots	Warmth, Failure recovery	Positive	None	None
Christoforakos et al. 2021	Humanoid service robots	Competence, Trustworthiness	Positive	None	None
Chuah et al. 2021	Robots	User preference	Positive and Negative	None	Personality traits
Crolic et al. 2022	Chatbots	Purchase intentions, customer satisfaction, firm evaluation	Negative	None	Emotional state
de Visser et al. 2016	Virtual agents	Trust resilience	Positive	None	None
Delgosha et al. 2020	Robots	Competence, predictability	Positive	None	None
Etemad-Sajadi et al. 2021	Robots	Usefulness, Trust, Intention to use	Positive	None	None
Ferrari et al. 2016	Social robots	Threat to human distinctiveness	Negative	None	None
Fink et al. 2013	Vacuum robots	Social presence	Positive	Decay of effect over time	None
Fraune 2020	Robots	Attitude, Moral behavior	Positive	Group membership	None
Gong 2008	Virtual agents	Social responses, Trustworthiness	Positive	None	None
Gursoy et al. 2019	Adoption of AI devices	Effort expectancy, emotion	Positive and Negative	None	None
Hildebrand and Bergner 2021	Chatbots, Robo-advisors	Trust, Firm perception, Recommendation acceptance	Positive	None	None
Hodge et al. 2020	Robo-advisors	Recommendation acceptance	Positive and Negative	Task complexity	None
Hu et al. 2021	AIAs	Continuance usage intention	Positive	None	None
Huang et al. 2021	Social robots	Identity threat, Usage intention	Negative	None	None
Jacobs et al. 2021	Robots	Acceptance of robots	Positive and Negative	None	Age differences
Kamide and Arai 2017	Robots	Comfortableness, controllability	Positive and Negative	None	Cultural differences
Kaplan et al. 2019	Robots	Tendency to anthropomorphize	Positive and Negative	None	Personality traits
Karimova and Goby 2020	AI-based products	Trust	Positive	None	None
Kim and McGill 2011	Slot machines	Risk perception	Negative	None	Social power
Kim and McGill 2018	Products	Agency, User evaluation	Positive and Negative	None	Financial status
Kompatsiari et al. 2021	Humanoid service robots	Socialness, Quality of interaction	Positive	None	None
Konijn et al. 2021	Robots in education	Learning, Enjoyment	Positive	None	None
Kwak et al. 2017	Robots	Purchase intention, Willingness to pay, Familiarity	Positive and Negative	Congruence of functions with design	None
Lefkeli et al. 2021	Robots	Mind scale	Positive and Negative	Cooperation vs. competition	None
Leichtmann et al. 2021	Robots	Social desirability	No effect	None	None

Li and Sung 2021	AIAs	Psychological distance	Positive	None	None
Liew et al. 2017	Virtual avatars	Website trust, information credibility, patronage intentions	Positive and Negative	None	Gender differences
Lin et al. 2021	Virtual salesperson	Social presence, Conflict	Positive	None	None
Liu and Tao 2022	Medical AI	Trust	Positive	None	Gender differences
McLeay et al. 2021	Service robots	Service experience, Usage intent	Positive and Negative	Role of service robot	Innovativeness, Openness
Mende et al. 2019	Humanoid service robots	Consumer discomfort, compensatory consumption	Negative	None	None
Mirowska and Mesnet 2021	AI evaluation	Objectivity of AI	Positive and Negative	None	None
Mishra et al. 2021	AIAs	User attitude, Usage	Positive	None	None
Müller et al. 2021	Robots	Identity threat, Distinctiveness	Negative	None	None
Pelau et al. 2021	AI service agents	Acceptance, Trust	Positive or No effect	Empathy and Interaction Quality	None
Pickard and Roster 2020	Virtual interviewers	Self-disclosure	Positive	None	None
Pitardi and Marriott 2021	AIAs	Social presence, Trust	Positive	None	None
Qiu and Benbasat 2009	Chatbot recommendation agents	Trust, Social Presence, Perceived Enjoyment, Intention to use	Positive	None	None
Reig et al. 2021	Robots, virtual agents	User preference	Positive and Negative	Time pressure	None
Rhim et al. 2022	Chatbots	Interaction time, user satisfaction	Positive	None	None
Schanke et al. 2021	Chatbots	Offer elasticity, Fairness	Positive and Negative	None	None
Schillaci et al. 2013	Robot movement	User satisfaction, Interactivity	Positive	None	None
Schuetzler et al. 2019	Conversational agent	Disclosure, Deception	Negative	None	None
Shank et al. 2019	Encounter with AI	Emotional reactions	Positive and Negative	None	None
Shin et al. 2019	Virtual avatars	Eeriness, Information processing	Negative	None	None
Sinha et al. 2020	Robots	Intention to use, Technophobia	Positive and Negative	None	None
Spatola et al. 2019	Social robots	Stroop task, Attentional control	Positive	None	None
Srinivasan and Sarial-Abi 2021	AI-algorithms	Penalization of brands for errors	Positive and Negative	Task type	None
Stanton and Stevens 2017	Robot gaze	Trust, Persuasion	Negative	None	Gender differences
Stapels and Eyssel 2021	Robots	User attitude	Positive and Negative	None	None
Striepe et al. 2021	Robots	User experience	Positive	None	None
Tang et al. 2021	AI-agents	Work performance	Positive and Negative	Task type	Personality traits
Tay et al. 2014	Social robots	User acceptance	Positive and Negative	Congruence of gender and personality with tasks	None
Thepsoonthorn et al. 2021	Robots	Affinity	Positive and Negative	Non-linear effect	None
van Dijk et al. 2013	Robots in education	Verb retention	Positive	None	None
Whang and Im 2020	Voice assistants	Product evaluation	Positive	None	None
Youn and Jin 2021	Chatbots	Behavioral intention, Trust, Satisfaction	Positive and Negative	Brand personality type	Ideological views
Yun et al. 2021	Medical AI	Intention to use	Positive and Negative	None	None
Zörner et al. 2021	Robots	Trust, Robot perception	Positive	None	None

AIA: Artificial Intelligence Assistant (e.g., Alexa).

the entity actually possesses a mind, but their behaviors are nonetheless shaped by the mind they

perceive. For example, despite knowing that an AIA, such as Alexa, cannot appreciate gratitude, many people say "Thank you, Alexa" automatically after completing a task with their AIA (Burton and Gaskin 2019). This response is triggered by the anthropomorphic features and is an example of people interacting with anthropomorphized entities as if they were social beings (Lopatovska and Williams 2018). Any attribution of a mind to an anthropomorphized entity exists relative to our own mind, and therefore might evoke an experience of a relationship (Novak and Hoffman 2019). For example, perceiving Alexa as covertly having sales goals for Amazon might elicit in the user an experience of a salesperson-customer relationship, or perceiving Alexa as capable of emotions might elicit kindness in user responses and create a (quasi) human-human relationship. Therefore, understanding exchanges between consumers and anthropomorphized AI from a relationship perspective could be insightful.

This proposition is in line with recent theoretical (e.g., Huang and Rust 2021a) and empirical (Uysal et al., 2022) work arguing that advanced AI could be used to form relationships with consumers and maintain them across time. By supplementing this perspective with relationship theories (e.g., social exchange theory) (Dwyer et al., 1987), we can conceptualize the interactions between consumers and anthropomorphized AI as an ongoing exchange of benefits and costs in a relationship. The exchange of benefits and costs will differ according to contexts as well as the individuals in question, leading to varying effects, as we have abundantly exemplified in this chapter. Each situation presents a unique relationship context and a different balance of benefits and costs for the consumer. For example, recent research has shown that AIA users who have been using their AIA for a longer time and for more personal tasks (e.g., organization of personal appointments) felt greater threat to their human identity as a result of AIA's anthropomorphism. However, users with a

shorter relationship tenure who use their AIAs mostly for menial tasks (e.g., turning on/off the lights) experienced such harmful effects to a lesser degree (Uysal et al. 2022). Therefore, a relationship perspective and the characteristics of such relationships between consumers and anthropomorphized AI could be pertinent in understanding the effects of anthropomorphism.

While our overarching recommendation of carefully studying the context and individual differences (Figure 3) remains the same, we believe that approaching this as an evaluation of potential benefits and costs in a relationship provides a useful theoretical outlook. This perspective creates a clearer understanding of the variations in many discrete effects that are documented in the literature.

FUTURE RESEARCH DIRECTIONS

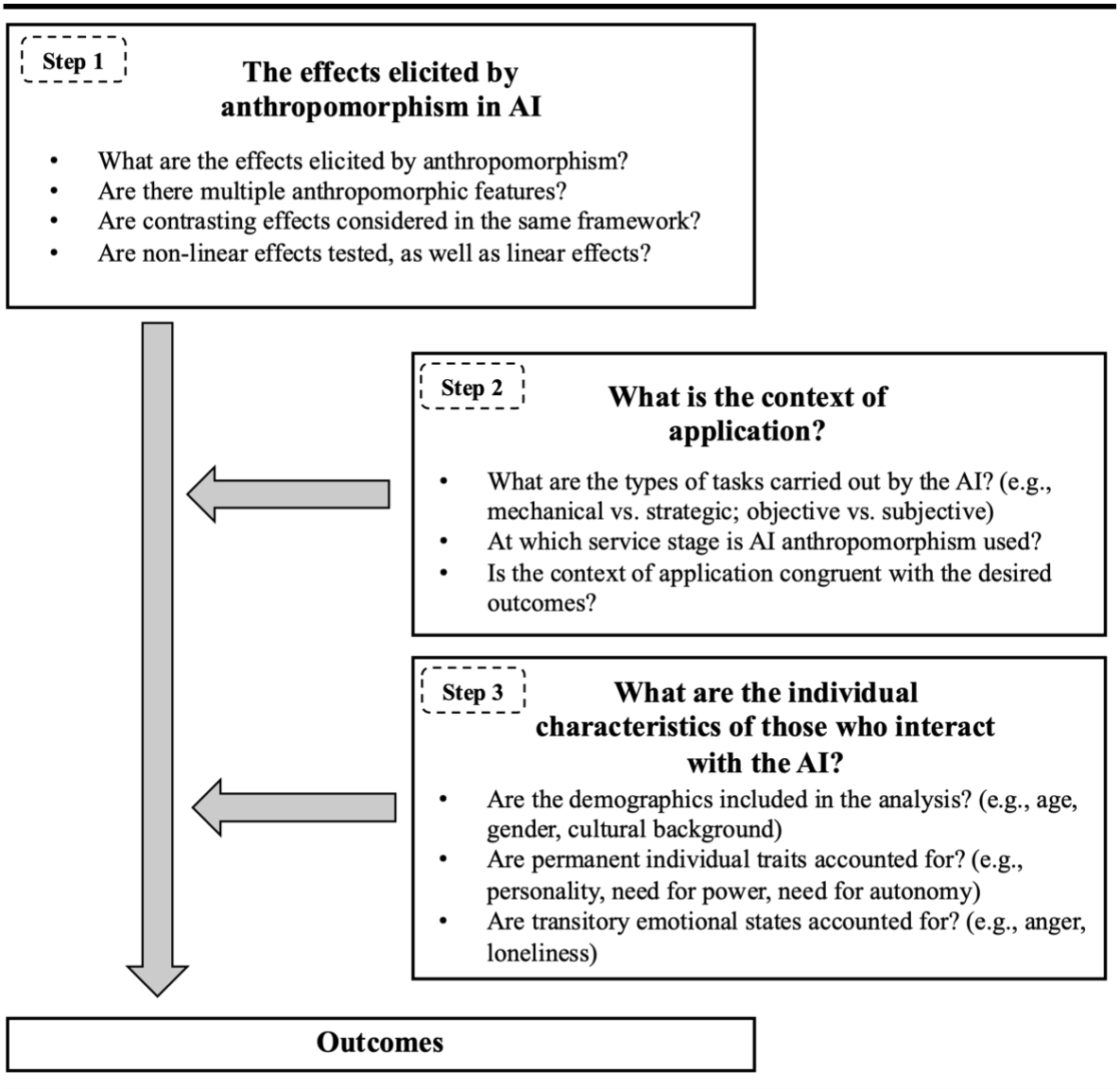
In this article, we have reviewed the literature on anthropomorphism in AI and proposed a framework to guide researchers and practitioners in the marketing and consumer behavior domains. We suggest that it is useful to benefit from this three-step analysis and taking a relationship perspective to achieve the highest accuracy in understanding the use of AI anthropomorphism in any particular case. Applying this framework will not only help achieve a clearer answer, but will also provide a parsimony in thought process by separating layers of analysis. We structure our discussion of future research in line with these three layers and develop distinct recommendations for each layer: (a) the valence of effects elicited by AI anthropomorphism, (b) the particular context and the task type carried out by the anthropomorphized AI, (c) the characteristics of the individuals that are exposed to anthropomorphized AI. Ideally, a future endeavor of research or practice should strive to take into account all three layers of analysis.

Future Research Directions Related to Effects of AI Anthropomorphism

Our first suggestion for future research is to have broader theoretical frameworks. Combining theories of anthropomorphism to include both potentially positive and negative effects will

provide a comprehensive outlook. Many of the articles in our review that showed positive effects rely solely on the anthropomorphism theory (Epley et al. 2007). While this is a valuable, well-established theory to understand anthropomorphism in AI, we see that the potential negative effects are disregarded in this theoretical framework. Theories relating to psychological costs such

Figure 3. The three-step framework as a guide for future research designs and practical implementations of anthropomorphism in AI.



as techno-stress, psychological strain and consumer ambivalence (Ayyagari et al. 2011; Edwards 1996) could be integrated into this framework to achieve a balanced perspective of anthropomorphism in AI. With that said, the same problem exists for the opposite stream of

research. We see that the articles that show negative effects also choose to zoom in too closely to the matter, relying on theories like uncanny valley and expectation confirmation theory (Mori et al. 2012; Oliver 1980). Similarly, while this is useful in unveiling important effects of anthropomorphism in AI, focusing only on that side disregards the big picture. Research shows that people reported many different positive and negative attitudes and behaviors concerning anthropomorphism in AI, this shows that they are actually being torn between two sides, perceiving both benefits and costs by anthropomorphizing the AI (Stapels and Eyssel 2021). Therefore, to capture this ambivalence, we suggest that utilizing a broader, inclusive theoretical framework is a must.

Second, most studies we reviewed have focused on adoption or intention to use. We suggest future research to investigate the effects of AI anthropomorphism on novel, untested outcomes that might be relevant for the firms such as willingness to pay for a product, purchase likelihood and the overall perception of the provider company. For example, AIAs such as Alexa are a good example of anthropomorphism in AI at a point of purchase and could be a promising avenue for future research. While there is good potential in AI anthropomorphism to be explored from a firm's perspective, a consumer perspective is still largely lacking in extant work. The range of application for AI is increasing tremendously and consumers are exposed to AI-powered devices for extended periods throughout the day. Seeing the pervasive and nuanced effects of AI anthropomorphism on people, we encourage future research to explore how consumers feel with regard to anthropomorphism in AI. It might be pertinent to assess the effect of AI anthropomorphism on consumers for outcomes such as well-being, privacy concerns and loneliness.

Moreover, similar to other technologies, anthropomorphism in AI may work well only in certain doses. While subtle anthropomorphic cues could elicit desired positive effects, abundantly endowing the AI agent with a variety of anthropomorphic features could elicit

opposite effects. Therefore, future research should explore the possibility of non-linear effects of AI anthropomorphism on relevant outcomes. Of course, this also brings the question about how different anthropomorphic features may elicit differing effects. Research shows that behavioral cues affect social attention while human-like appearance induces greater mind perception ratings (Abubshait et al. 2021). Therefore, endowing a human-like body, movement or speech to an AI agent could all have different effects on people and might even work in opposite directions. We suggest future research to build a taxonomy of anthropomorphism to understand exactly which cues impact which outcomes.

Future Directions Related to the Context of Employing AI Anthropomorphism

Our first suggestion for future research in relation to the context of using anthropomorphism in AI is about the task types carried out by the AI. Different types of tasks are entrusted to AI strategically: while "mechanical" AI could do well with repetitive actions, "thinking" AI could be used for decision making by data processing (Huang and Rust 2021b). Therefore, future research should prioritize investigating the potency of anthropomorphism in AI that is used in different types of tasks. While anthropomorphism might be redundant or even incongruent for an AI agent that is entrusted with repetitive, mundane tasks, it could be much more effective, for instance, in human-AI interactions. Moreover, a perception of humanness in an AI agent might be beneficial in a symbolic consumption context where consumers typically prefer human (vs. robotic) labor (cf. Granulo et al. 2021). The human likeness exhibited by the AI agent should be a good fit for the task it carries out. Therefore, we advise against using anthropomorphism in AI for the sake of using it. In a suitable context it could be beneficial for the firms and the consumer experience, but an arbitrary use could lead to unforeseen effects.

Second, future research should explore whether anthropomorphism in AI is particularly useful in a certain stages of the customer journey. For example, anthropomorphic features could be more advantageous at the pre-purchase stage where the customer is looking for purchase

recommendations. The trust elicited by the anthropomorphic cues could result in higher rates of heeding to purchase recommendations. On the other hand, at the post-purchase stage when the customer has a problem or a complaint, refraining from anthropomorphic cues in an AI customer service could be a better idea. While there is nascent evidence in the literature that provides us with these examples (Garvey et al. 2021; Hildebrand and Bergner 2021), further research is necessary to be able to leverage anthropomorphism in AI optimally in pre-purchase, purchase and post-purchase settings. In addition, we discussed in the previous section that human-AI interactions could be conceptualized as a relationship, if the AI agent is anthropomorphized (Uysal et al. 2022). Therefore, integrating relationship theories (e.g., Dwyer et al. 1987) into the study of AI anthropomorphism and drawing parallels from relationship marketing to explore a relationship lifecycle account of human-AI interactions provide a novel lens through which AI can be explored. Analogous to the relationship lifecycles idea, future research could investigate the particular human-AI relationship trajectories and the efficacy of anthropomorphism in different relationship stages. For example, based on recent research on Artificial Intelligence Assistants (AIA) (e.g., Alexa) (Koike and Loughnan 2021), the experiential value that is brought by the anthropomorphic nature of the AIA might fade away over time, while the perceived functional value remains largely unchanged (see Fink et al. 2013 for a similar effect in vacuum robots). This hints at the possibility that anthropomorphism in AI could be more potent earlier in a human-AI relationship (i.e., exploration phase) (Jap and Ganesan 2000).

Future Directions Related to Individual Characteristics of AI Users

So far, most studies have included individual characteristics as control variables and have reported them as footnotes. However, our review of the literature shows that the impact of individual characteristics is far from trivial. In several studies, we have seen that age, gender and cultural differences could impact the effect of AI anthropomorphism greatly, sometimes

even reverse the effect (e.g., Jacobs et al. 2021; Kamide and Arai 2017; Liu and Tao 2022). However, a differentiation based on such basic features could oversimplify individual characteristics. We suggest future research to consider individual characteristics more seriously and systematically explore their role in the perception of AI anthropomorphism. Individuals' personality (e.g., big five dimensions) and psychological attributes such as need for personal space, need for autonomy or self-construal and need for touch should be investigated in combination with age, gender and culture. Only a combination of individual features could lead to the most accurate description of individuals' tendencies in relation to AI anthropomorphism.

In general, the anthropomorphic features seem to be selected arbitrarily in most studies. We see that in many studies with embodied robots, the design is completely random and each study have a different robot used in their experimental procedures. Simply building a body, face, arms and legs is assumed the make a human-like entity. However, every detail of a human-like entity is likely to elicit a different effect. In line with the expectation confirmation and affordance theories (Gibson 1977; Oliver 1980), each observed quality hints at an affordance. We perceive the world, in a way, in terms of possibilities for action. Endowing a non-human entity with certain anthropomorphic characteristics signals such possibilities. If a robot has legs, people assume the possibility of locomotion. If a robot can speak in natural language, people assume that it can understand and reply like a human being. It is when these expectations are not met that the problem arises (Lankton et al. 2014). Our suggestion to tech designers is to be cognizant about the congruence of the of the anthropomorphic features with the use context and use those features only if they can satisfy the hinted expectations.

Essentially, future research should prioritize an investigation of contingencies and boundary conditions. In recent years, AI has been deployed in many distinct contexts from carrying out job interviews and medical analyses to acting as service agents and salespeople. It is difficult for people to allow to delegate many routine tasks in their daily lives, let alone

sensitive, high-stakes ones. Endowing the AI with anthropomorphism seems like a great opportunity to curb the resistance against adoption of AI by acting as a buffer against people's biases. Managers and tech designers should think carefully about what AI represents and what anthropomorphism represents. In contexts where precision, accuracy and impartiality is prioritized, a human likeness may be omitted, and in contexts where an affinity and social presence is required, anthropomorphism can provide an advantage. Without a coherent framework to understand these conditions, new studies will continue to argue for positive and negative effects of AI anthropomorphism in an isolated manner. Therefore we suggest that the framework we propose can be a useful practical guide in the implementation of anthropomorphism in AI. Moreover, taking a relationship perspective in conceptualizing the interactions between consumers and anthropomorphized AI could pave the way for future research that aims to understand the generalizability of the effects of AI anthropomorphism.

Finally, AI anthropomorphism could play a large role in accurately conceptualizing the role and acceptance of latest AI technologies to our daily lives. Many people hold concerns over whether advanced AI will gradually displace humans not just in mechanical tasks, but also in tasks that require thinking and feeling. One reason for this concern could be the perceived incongruence between the nature of AI and the tasks it is entrusted with. Anthropomorphism, if used prudently, could help bridge this man-machine gap and lead to greater acceptance of AI in our lives, even in tasks that are thought to be reserved for humans (i.e., thinking, feeling). However, a second reason for this concern could be the perception of an intelligent, rival mind in the AI. Being in a psychological competition with AI would question our human nature and our role in the digital world. In this case, any attempt of instilling human likeness in AI which reinforces this mind perception will be counterproductive. A fear of being replaced by a competing artificial mind could drastically change the public attitude towards technology and

innovation (Davenport et al. 2020). Therefore, it is essential to understand the role of anthropomorphism in AI thoroughly.

LIMITATIONS

Despite carefully following guidelines for a systematic review, our paper is not without limitations. We limited our scope to empirical journal articles that appeared in the selected journals and did not include any conference proceedings and working papers. In an emerging topic such as anthropomorphism in AI, there is an exponential growth in the number of publications over the last years particularly in conference proceedings. Therefore, the article count in this review may be smaller, but has the advantage of including only high quality research. It is difficult to systematically include all working papers and much harder to assess their quality. Moreover, there are many recent thought-leading conceptual articles on human-AI interactions which are harbingers of groundbreaking research over the next years (e.g., Huang and Rust 2021b; Novak and Hoffman 2019; Puntoni et al. 2021). In our review, we do not account for these conceptual papers because we purposefully wanted to explore what the data shows about the use of anthropomorphism in AI.

Second, many studies we have reviewed have adopted disparate methodological directions. For example, while some studies rely on online consumer surveys (e.g., Mishra et al. 2021), other studies have carried out laboratory experiments (e.g., Mende et al. 2019). They are essentially different in the sense that participants, in the latter case, might interact and engage with the anthropomorphic AI first hand. Moreover, the design of the stimuli (i.e., robots, virtual agents) hinges on the individual research group. This results in arbitrarily different anthropomorphic designs in each study which reduces comparability of results across studies. Future research could benefit from meta-analyses that compare the empirical work specifically according to their methodological choices.

CONCLUSION

In this review, we attempted to synthesize insights on anthropomorphism in AI. By reviewing 69 articles that were filtered among 287 articles from 39 leading journals across computer science, robotics, psychology, marketing and consumer behavior fields, we offer a greater understanding of the knowledge of anthropomorphism in AI, which currently lacks a coherent framework to organize the identified effects. To this end, we developed a conceptual framework of three sequential steps, aiming to provide a starting point to explore the nuanced effects of AI anthropomorphism in a systematic way. This conceptual framework offers many future directions to explore. Since anthropomorphism is being used increasingly frequently in AI agents that face the consumers, our review and the conceptual framework contribute to the discussion on how to best utilize this strategy. Particularly for marketing managers, our conceptual framework identifies a key take-home message: there could be great promise in employing anthropomorphism in AI wisely, but a careless use may undermine the potential of cutting-edge new AI technologies for both consumers and firms.

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CHAPTER 3

ESSAY 2: Trojan horse or useful helper? A relationship perspective on artificial intelligence assistants with humanlike features

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INTRODUCTION

Artificial intelligence assistant (AIA) users have surpassed 100 million in the US alone (Bohn 2019). They are the latest artifacts of the digital age that aim to enhance comfort, and they constitute a selling platform in consumers' own homes (e.g., Amazon's Alexa). Critically, AIAs are endowed with cutting-edge artificial intelligence (AI) technology, giving them the capacity to naturally interact with their users (henceforth, consumers) in a humanlike way. Seeing the close personal interactions inextricably intertwined with the powerful AI technology, some consumers perceive AIAs as social actors with a mind of their own, that is, they are anthropomorphizing the AIAs (e.g. Foehr and Germelmann 2020). Moreover, only recently has such a cutting-edge AI-based device been so pervasively and centrally implanted in households, leading consumers to interact daily, and eventually to attribute to this hardware companion a mind of its own. As a result of such anthropomorphism, consumers may build personal relationships with their AIAs with the upsides of relationships such as elevated customer service and satisfaction, but also some potential downsides. The paper's core goal is to examine consumers' relationship with the AIAs that are embedded in smart speakers, and investigate beneficial and harmful effects of anthropomorphizing AIAs on consumers' satisfaction and well-being.

Past research conceived anthropomorphism in AI in a favorable light, focusing mostly on consumer benefits. Anthropomorphism in AI has been established as a path to elicit trust in

robots and virtual agents (e.g., Lin et al. 2021), as well as in AIAs (e.g., Foehr and Germelmann 2020). However, more recently, seminal conceptual works on AI have proposed the idea that relationships with AI in service contexts may actually prove harmful to consumers (Pfeuffer et al. 2019). For instance, AIAs can exhibit an invasive nature into consumers' privacy, and store and analyze consumers' most personal data which can cause mental strain for consumers (Puntoni et al. 2021). But these past works are primarily of a conceptual nature and to date, no research has empirically explored in detail the potential psychological costs for consumers who anthropomorphize their AIAs. Thus, it seems worthwhile to examine the harmful effects of AIA anthropomorphism (i.e., perceiving a mind within an AIA) on consumers (see Table 1 in the paper for a synthesis of this literature, and Figure I in Appendix C for the main research model in light of past literature).

AIAs, such as Alexa, accompany consumers across a large part of their waking and even sleeping hours, often over several years, and, as a result, may assume a key role in consumers' daily lives. In other words, consumers are forming close relationships with AIAs that may expand over time. As relationship marketing research unequivocally shows, relationship development builds on gaining benefits, but likewise incurring costs from the relationships (Dwyer et al. 1987). Gaining a comprehensive understanding of those costs in terms of psychologically harmful effects for consumers in a relationship with their AIA is paramount from a research, practice, and societal perspective.

To examine benefits as well as costs for consumers in relationships with AIAs, we draw on a seminal relationship theory, social exchange theory (Blau 1986; Homans 1961), and blend it with mind perception theory (Gray et al. 2007) (see Figure II in the Appendix C for a depiction of this integration). Specifically, we propose that when consumers perceive a mind in their AIA (i.e., they anthropomorphize it), they are more likely to form relationships with their AIAs and to apply a cost–benefit approach to this relationship. Perceiving a mind in the

AIA thus leads to both benefits and costs for the consumer, constituting two mediating mechanisms for the effects of AIA anthropomorphism. In addition to the well-established beneficial path through trust in the AIA, we argue that AIA anthropomorphism affects key consumer outcomes by triggering greater consumer privacy concerns and diminishing consumer satisfaction and well-being through an increased feeling of threat to human identity. Moreover, we essentially argue that AIAs' threat to human identity can lead consumers to feel disempowered, again harming their well-being. Importantly, drawing on social exchange theory and its relationship perspective, we suggest that these harmful effects are more pronounced if consumers have a closer and longer-lasting relationship with the AIA. Figure 1 depicts our conceptual framework.

We conducted two full studies, as well as preliminary interviews and a preliminary consumer survey. In Study 1, we surveyed 238 current users of AIAs embedded in smart speakers at home (e.g., Amazon Echo, Google Home) and demonstrated a harmful path emerging from AIA anthropomorphism, as well as replicating the beneficial path. Our key finding in Study 1 is that AIA anthropomorphism triggers consumers' privacy concerns through an increased feeling of threat to human identity. Subsequently, consumers' privacy concerns decreased their satisfaction and well-being. Building on this key finding, we conceptualized and tested remedy strategies to alleviate these harmful effects in a second study, a field experiment with 601 current AIA users. We implemented one control condition and three interventions: (1) raising consumers' awareness about AIA data practices, (2) providing consumers with knowledge on how to deal with AIA data issues and (3) requesting consumers to take action to protect the privacy of their data in their relationship with the AIA. We measured consumers' responses across two different time points and found that these interventions successfully attenuated the harmful effect of threat to human identity on

consumer AI empowerment, subsequently improving consumer well-being and reducing privacy concerns.

With these findings, we argue for two main theoretical contributions. First, these findings contribute to the literature on human–AI relationships by investigating (to our knowledge for the first time) the usage and interactions with AIAs through a relationship lens. While past research has primarily used a stimulus–response approach to examine consumers' immediate reactions to AIAs (e.g., Benlian et al. 2020), owing to the unique place of AIAs in a consumer's home and an intensive exchange of benefits and costs, we suggest that a relationship perspective is valuable for investigating AIAs. Specifically, integrating relationship theories (e.g., Dwyer et al. 1987) into the study of AIAs and drawing parallels from relationship marketing to explore a relationship lifecycle account of human–AI interactions provide a novel lens through which AIAs can be explored. Exploring the relationships between the consumers and the AI-powered platforms can unveil versatile interactions that go beyond purchases and foster consumer loyalty. The relationships that consumers form with intermediary platforms such as Alexa may gradually replace the traditional consumer–firm relationships. Second, we contribute to past literature (Table 1) by providing a more balanced account of benefits and potential psychological costs of AI for consumers. While the benefits of anthropomorphism in AI technology are well documented in the literature, a closer look at this phenomenon shows that there are psychological costs experienced by the consumers in the relationship with AIAs. Considering the ambivalent effects of AIAs on consumers unveiled by our study, we suggest that it might be pertinent to leverage theories related to psychological costs and consumer ambivalence (e.g., techno-stress, cognitive appraisal) when investigating anthropomorphism in AI. Established theories of anthropomorphism (e.g., Epley et al. 2007) could thus be meaningfully extended by including

Table 1. Prior experimental work on the effects of AIA anthropomorphism.

Authors	Context	Discussed Effects of Anthropomorphism	Key Dependent Variables Discussed	Relevant Findings & Insights
Foehr and Germelmann 2020	AIAs	Beneficial	Trust in the AIA	Alongside other paths to trust, this study shows that AIAs' humanlike personality is a path to foster trust in the consumer.
Li and Sung 2021	AIAs	Beneficial	Psychological distance with the AIA	When anthropomorphism of the AI assistant was high, participants had more positive attitudes toward the AI assistant, mediated by psychological distance with the AIA.
Pitardi and Marriott 2021	AIAs	Beneficial	Trust in the AIA, Attitude towards AIA	This study shows that social presence of the AIAs improved the consumers' attitude towards the AIA through increasing trust felt towards the AIA.
Moriuchi 2021	AIAs	Beneficial	Intention to Adopt	Greater perceived anthropomorphism of the AIA predicted higher intention to adopt the technology through greater engagement of the consumer.
Mishra et al. 2021	AIAs	Beneficial	Attitude, Usage, Satisfaction	Anthropomorphism was positively related to utilitarian attitudes held towards the AIAs. Mediated by utilitarian attitudes, greater perceived anthropomorphism of the AIA increased frequency of AIA use and satisfaction with the AIA.
Benlian et al. 2020	AIAs	Beneficial	Psychological Strain	Anthropomorphic design features can mitigate the adverse effects of the invasion of users' privacy created through invasive AIA features.
Poushneh 2021	AIAs	Beneficial	Consumer Satisfaction	Anthropomorphic personality features in the AIA increased consumers' perceived control over the AIA, which in turn indirectly increased consumer satisfaction with the AIA and consumers' willingness to continue to use the AIA.
Ferrari et al. 2016	Social robots	Harmful	Threat to human identity	High degree of anthropomorphism in robots leads to undermining human-machine distinctiveness and subsequently to a feeling of threat to human identity.
Mende et al. 2019	Humanoid service robots	Harmful	Threat to human identity	Highly anthropomorphized humanoid service robots lead to a feeling of threat to human identity.
Appel et al. 2020	Humanoid service robots	Harmful	Feeling of eeriness	A robot's capacity to feel (but not agency) elicits stronger feelings of eeriness.
Stein and Ohler 2017	Virtual agents in virtual reality	Harmful	Feeling of eeriness	Emotionally anthropomorphic autonomous virtual agents (in VR) elicit stronger eeriness in participants, by blurring human-machine distinctiveness.
Our Paper	**AIAs**	**Beneficial and Harmful**	**Trust in the AIA, Threat to Human Identity, Consumer Well-being, Consumer Empowerment**	**Anthropomorphism elicits consumer trust, but also a human identity threat. This identity threat reduces consumer well-being through reducing consumer AI empowerment. Raising consumers' awareness about privacy issues and solutions and urging them to take action for their privacy alleviates the harmful effect of identity threat on empowerment.**

Note: For the sake of brevity, articles reporting similar effects with the same dependent variables were not included in this table.

in their framework the psychological costs, as well as the benefits, generated in interactions of humans with anthropomorphized AI entities.

The results of our study show that if managers endow AIAs with anthropomorphic features, it entails ambivalent effects such that consumers are more satisfied with the AIA, but at the same time, experience less general well-being. Therefore, our first recommendation to managers is to endow AIAs with anthropomorphism only if their respective customers are knowledgeable and confident about protecting their privacy in the relationship with the AIA. While there could be great promise in employing anthropomorphism in AI prudently, an indiscriminate use could undermine the potential of such cutting-edge AI technologies for both consumers and firms. Second, to minimize the harmful effects of AIA anthropomorphism and maximize its benefits, managers should empower consumers regarding the protection of their personal data. We provide managers with three practical ways of empowering users to competently handle their data security which could lead to an increase in purchases and customer relationship building through this unique channel.

Preliminary Insights on Consumers' Relationships with Artificial Intelligence Assistants

Public opinion about the AIAs seems to be mixed: AIAs seem to polarize consumers such that some consumers joyfully use them, while others express blatant rejection, even avoiding being around AIAs. We conducted two preliminary studies with two key goals: (1) to gain and present an up-to-date overview of users' opinions on AIAs in a systematic way, and (2) to understand the prevalence and the extent of consumers' privacy concerns and relationship issues with AIAs. To this end, we measured the consumers' perceptions with a survey, and conducted interviews with AIA users.

Preliminary consumer survey

We conducted a preliminary consumer survey with 300 (M_{age}=31.6, 68% female) participants recruited from Prolific to assess the extent of consumers' concerns about the privacy of their

personal data collected by the AIAs and their knowledge of how this data might be used. We found that, although AIA users have a high level of general concern related to personal data (M=5.43) and think that AIAs are intrusive (M=5.06, both measured on seven-point scales), their knowledge of, and tendency to take action to protect, their privacy are very limited. We found that only 20% of AIA users know where their data goes and who has access to it, 65% of the users have never changed their privacy preferences and 85% of the users never reviewed or deleted their stored voice recordings. Remarkably, 49% of the AIA users in this survey tend to agree with the statement that companies are currently exploiting consumers with new AIA platforms. This preliminary survey indicates that there may be looming issues in consumers' relationships with AIAs: they express high privacy concerns but know little about how their data is handled and typically do not take action (i.e., they seem disempowered).

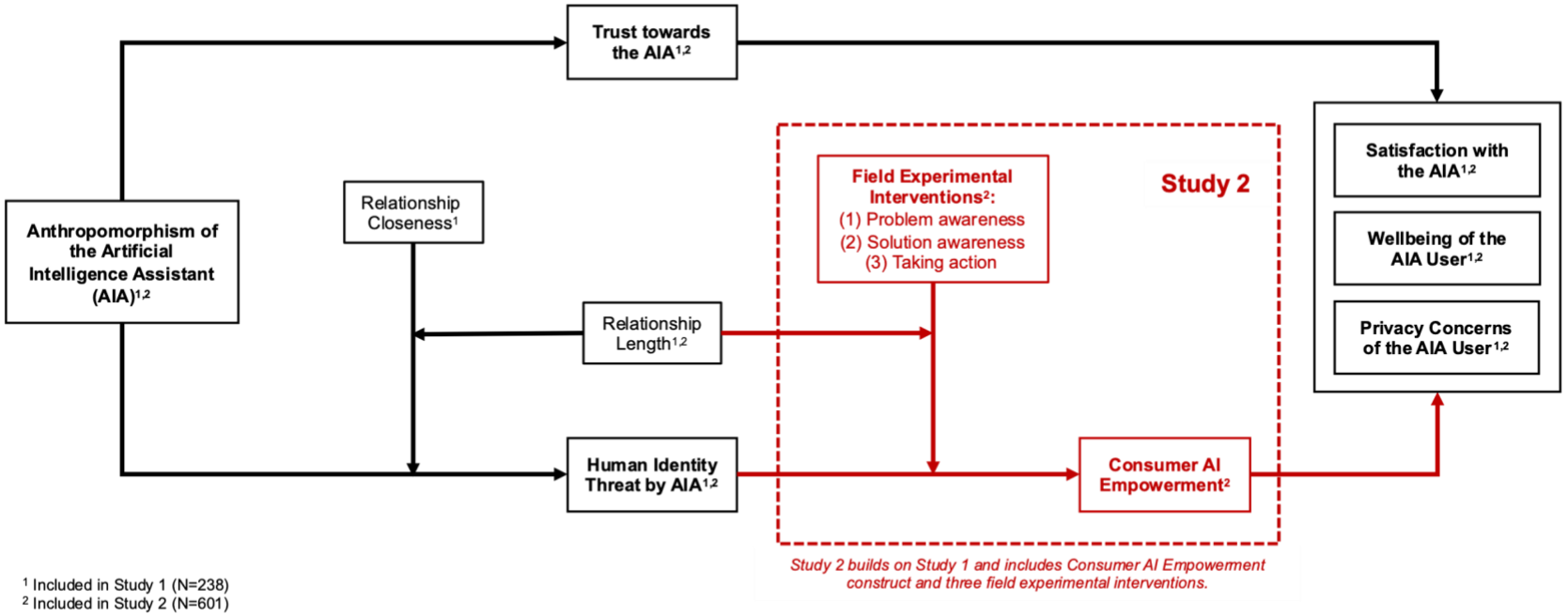
Preliminary interviews

To acquire a deeper, more specific initial understanding of AIA–user relationships, we conducted 11 in-depth interviews totaling 5 hours and 30 minutes of interviews. Results show that users perceive clear and salient benefits from AIAs, but also deliberate on costs and risks (N=4). There is a strong awareness of an always-listening device, occasionally leading the consumer to think about whether the next thing they utter will be heard and recorded by the AIA (N=3). As user D states in the interview, *"There are certain situations where I think 'this does not need to be on tape'[…] and turn her off."* For some users the reason for substantial privacy concerns is their lack of knowledge (N=3), which corroborates the results of the preliminary consumer survey. User A notes, *"I do not even know what functions the device has […] I am not sure if certain functions are too unsafe."* While seeing clear benefits in the convenience that AIA brings, consumers were also nervous about instances of AIA behaving autonomously, seemingly acting of its own volition (N=4). The interviews also informed us

Table 2. Insights from preliminary interviews.

Category	Representative Quotes
Benefits of Consumer-AIA relationships	"Alexa gives me more free time. It is like she is supporting me […]" (F, 14:53) "She is powerful because she has many functionalities and can do many things […] but she is not powerful in the traditional sense so that she is controlling me or prescribing me things" (E; 26:54)
Ambivalent Perceptions of Consumer-AIA relationship	"I do like it because it is helpful but sometimes some strange things happen. Sometimes it starts singing without anything happening around and you think what is going on? That is kind of strange but in general it is helpful (J, 3:31) "[I would describe it as an] ambivalent relationship because Alexa is great with regard to a family factor, especially the opportunity to play music via Alexa […]. But from a data protection perspective, I am critical towards it" (K, 4:03) "Yes, definitely […] I think some jobs will be replaced but many things get easier and they [AI] are opening new windows of opportunity" (E; 25:10)
Negative Perceptions of Consumer-AIA relationship	**Privacy Concerns** "I know that there is a silent listener […] we have a big house […] but she can hear us talking in most of our rooms" (C; 29:20) "I would not say that an AI could threaten us, but I would say […] that they gather data that feed algorithms in order to create personalized advertisements. And this is data that is used to create capital […] So I don't see a threat but the chance of exploiting it [the gathering of data]" (A, 10:00) "I do not even know what functions the device has....I think that I still have an uncertainty about how it works with the purchases and whether it is too unsafe […] I would say that the device does not always understand you well and as soon as it comes to shopping, for example, I am afraid to touch such functions." (A, 3:36) "If I read something to my daughter and she [Alexa] talks in between, she is turned off. And if I feel to be controlled too much by her she is turned off as well. So there are certain situations where I think "this does not need to be on the tape" (K, 20:40) **Human Identity Threat by & Fears** "A threat is that the mankind is isolating itself and takes care of machines and maybe is going to communicate more with these […] the human gets lost" (I; 13:25) "AI is taking the upper hand […] Especially children and teenagers are on the cell phones. I think that there is a great danger […] because many of them become lonely" (C, 24:10) "[Alexa is] a little bit threatening. Because she is understanding certain things and you're not thinking about it while speaking all the time […] After talking about it for a longer time you get aware of it" (J; 30:00) "All those technologies might change the structure of the society" (J, 39:00) "The role [of AI] is difficult because too many jobs are going to be lost as a result […] humans are being replaced too much by technology." (G; 8:30) "If I look at the world of work and how much human intelligence is replaced by AI […] it is something that increases efficiency for companies, but ultimately costs human jobs." (K, 15:40)

Figure 1. Overview of the conceptual model.



Note: The field experiment comprised one control condition and three interventions. With the interventions, we intended to (1) rais e consumers' awareness about AIA data practices, (2) provide consumers knowledge on how to deal with AIA data issues, and (3) urge consumers to take action to protect the privacy of their data in their relationship with the AIA.

about the kind of costs that consumers may experience in their relationship with AIAs. Many consumers expressed fears regarding the potency of AI and referred to AI as a competitor to humans, essentially seen as an undesirable replacement for humans rather than as an enhancer of human experience (N=6). Table 2 provides a selection of relevant quotes from the interviews. Further details about the preliminary studies can be found in Appendices C and D.

These two preliminary studies show that AIA users hold ambivalent opinions about their AIAs and know little about how their data is used by the AIAs. Also, privacy concerns in the human–AIA interaction seem to be common among users. To investigate this further, we next present a conceptual framework and then two full studies.

THEORETICAL FRAMEWORK

Integrating mind perception theory and social exchange theory to build a user–AI relationship perspective

In what follows, we integrate mind perception theory and social exchange theory to build a relationship perspective on user–AI interactions and exchanges (see Figure II in Appendix C). In this respect, social exchange is the main theoretical backbone. Social exchange theory describes how individuals form relationships with others and which factors determine the subsequent relationship development. A key assumption is that all human relationships form on the basis of a subjective cost–benefit analysis (Homans 1961). In other words, the benefits and costs which individuals perceive in a relationship determine whether individuals initially engage in the relationship and whether they uphold the relationship (Emerson 1981). Conversely, if exchange partners view the benefits-to-costs ratio in a relationship as insufficient, they will likely terminate the exchange relationship.

Recent literature suggests that advanced AI might be used to engage consumers in the service journey, form relationships with consumers and maintain them across time (Huang and Rust 2021a). However, theory of mind perception is essential to understand user–AIA

exchanges and interactions from a relationship perspective (Gray et al. 2007; Epley and Waytz 2010; Waytz et al. 2010). According to mind perception theory, people infer that others have mental states that are different than their own and are capable of attributing minds to others. Importantly, people assign minds not only to other people, but also to non-human entities such as animals, gadgets or software and respond to them using the same social rules that they use with people (Epley and Waytz 2010; Nass and Moon 2000). Since people do not have direct information of others' mental states, a social exchange *requires* mind inferences about the contents of other individuals' mental states, especially their desires, goals and intentions (Cosmides and Tooby 1992). Therefore, based on their observations, people make inferences of the mental states of others (e.g., if it talks and looks like a human, then it must have desires and intentions like a human). However, in doing so, people do not actually believe that an anthropomorphized entity is human but rather the anthropomorphic features such as natural language and interactivity trigger responses that are guided by human social rules. Thus, in many ways people interact with AIAs as if they were social beings and the AI-powered anthropomorphic assistants could form and maintain relationships with the consumer by improving themselves constantly to adapt to the consumer, thanks to the constant availability of personal data, in a way similar to sales agents who may form and maintain relationships with their customers (Schmitz et al. 2020).

The motivation for this tendency to assign a mind to non-humans stems from the desire to understand and predict their behavior more easily, and to establish contact and affiliation (Epley et al. 2007). Assigning a mind to a non-human increases the perceived similarity of the human and the non-human entity. While the perceived similarity with the AIAs (i.e., the perception of an intelligent, competent mind of the AIA which is humanlike) brings about some benefits such as a greater sense of trust, closeness and enjoyment towards the entity (Li and Sung 2021; Qiu and Benbasat 2009), the same perception can evoke psychological costs: it

triggers a feeling of threat to human distinctiveness, raises doubts about one's place in the world and introduces a fear that humans could be replaced by non-humans with intelligent minds (Złotowski et al. 2017). That is, while a mind that can support the consumer by helping and serving might be desirable, at the same time it could be rivaling and threatening. Such ambivalence is common in human relationships. Consider a manager who holds an employee in high esteem and trusts the employee in task fulfillment, but at the same time fears that this excelling employee might one day take over his/her job. Thus, integrating mind perception and social exchange theories, we argue that when consumers perceive a mind in their AIA (i.e., they anthropomorphize it), they apply a social exchange framework, that is, they adopt a cost/benefit view of the relationship with their AIA. Those who have a greater perception of an AIA's anthropomorphism will see greater benefits in the relationship with the AIA, but also higher costs.

Beneficial effects of relationships with artificial intelligence assistants

Previous work has shown that anthropomorphizing robots, computers and even brands, attributing a mind to them, fosters trust towards them (Golossenko et al. 2020; Hildebrand and Bergner 2021; Nass and Moon 2000). Attributing a mind to a non-human agent increases people's perception of the agent's competence (Waytz et al. 2014). A competent AIA mind that exists to help and serve, with benevolent motives and positive intentions, can create trust in a relationship (Foehr and Germelmann 2020). Having a supportive mind that seeks to assist humans is a clear benefit that AIAs provide to consumers. Gaining such a benefit in a relationship engenders trust in the AIA. In turn, decades of marketing research has shown that customers' trust in a firm or service employee increases customer satisfaction (Hennig-Thurau et al. 2002; Singh and Sirdeshmukh 2000).

H1 (replication hypothesis) Higher (vs. lower) AIA anthropomorphism increases consumer satisfaction through elevated trust in the AIA.

In our work, we seek only to briefly replicate this well-established beneficial path through trust and focus on the potentially harmful path through identity threat.

Harmful effects of relationships with artificial intelligence assistants

In what follows, we elaborate on the effect of AIA anthropomorphism on consumers' perceived identity threat. For this purpose, we strongly draw on theory of mind perception (Gray et al. 2007). Critically, we argue that consumers will experience psychological costs which arise from perceiving a mind in the AIA. A perception of increased similarity with the AIA, while providing benefits, is not compatible with the conception of human distinctiveness (Ferrari et al. 2016). Therefore, attributing a mind to a non-human entity – a feature that is thought to be uniquely human—might trigger a feeling of threat to human identity. We define this feeling of threat to human identity as a worry that the AIAs might challenge human uniqueness, raising doubts about one's place in the world and a fear that humans can be replaced by non-humans with rivaling intelligent minds (Gray and Wegner 2012; Mori et al. 2012; Yang et al. 2020). Feeling a threat to human identity implies that consumers perceive the AIA as conflicting to the established human ways, opposing human core values.

We now turn to our explanation of why the identity threat from AI should trigger privacy concerns regarding AI's data use in the relationship. In essence, the threat to human identity arises from perceiving an artificial mind in the AIA. This artificial mind exhibits an awareness of its surroundings and can have intentions and motives of its own, and importantly, it tracks its surroundings, rendering it as data, storing and analyzing the data using its AI (Kozinets and Gretzel 2021). The perception of this competent artificial mind creates increased uncertainty about AIAs' behaviors, motives and intentions. We define this uncertainty in the human–AIA relationship as not knowing exactly the motives and intentions of the AIA, therefore not knowing how to engage with and react to AIAs. Being increasingly aware of a

competing artificial mind that deals with our personal data and limits our autonomy to control the fate of our personal data interferes with maintaining a sense of privacy.

H2 Higher (vs. lower) AIA anthropomorphism increases privacy concerns by elevating the perception of artificial intelligence's threat to human identity.

In what follows, we focus on explaining why the AIA anthropomorphism-induced threat reduces consumer satisfaction with the AIA. A threat to our human identity puts us in a state of uncertainty and might elevate our stress levels (Higgins et al. 1994; Sharma and Sharma 2010). This increased uncertainty in the human–AIA relationship, not knowing exactly the motives and intentions of the AIA, puts a strain on the consumer that presents a significant psychological cost. In a social exchange framework where consumers weigh benefits and costs, this added psychological cost induced by perceiving a mind in the AIA deteriorates the balance of benefits and costs. Therefore, as soon as the psychological costs in the relationship increase, consumer satisfaction with the AIA should diminish.

H3 Higher (vs. lower) AIA anthropomorphism reduces consumer satisfaction by elevating the perception of artificial intelligence's threat to human identity.

Next, we will present our reasoning as to why AIA's anthropomorphism reduces consumer well-being through increased feeling of threat to human identity. Threat to human identity induced by perceiving a mind in the AIA should lead the individual to experience psychological discomfort in the relationship with the AIA (Breakwell 1986). More specifically, the consumer is in a state of uncertainty in the relationship with AIA, doubting and questioning his/her identity. This unfavorable mental state created by the identity threat could engender negative feelings and elevate stress in the consumer, thus reducing the well-being of the consumer (Sharma and Sharma 2010). Therefore, we hypothesize:

H4 Higher (vs. lower) AIA anthropomorphism reduces consumer well-being by elevating the perception of artificial intelligence's threat to human identity.

Moderating effects of relationship characteristics

Social exchange theory suggests that relationship closeness and relationship length are key determinants of relationship development (Palmatier et al. 2006). With increasing relationship length, the bond of social exchange gets stronger and the benefits-to-cost ratio becomes more salient for the consumer (Gundlach et al. 1995). However, relationship length alone might not be sufficient to establish a close relationship. Dependence of the partners on each other constitutes another key factor to grow a close relationship (Ganesan 1994). Essentially, AI-powered entities can learn from consumer interactions over time to improve their accuracy, thereby strengthening the relationship with the consumer (Marinova et al. 2017). Applying this to AIAs, consumers might become dependent on and close to the AIA if they consistently use it for important personally consequential tasks, such as organization of personal appointments or self-management. While the consumers who have more recently adopted an AIA or those who use their AIA largely for menial tasks (e.g., turn on/off the lights) may still perceive the AIA as a trivial gadget for convenience, an extended use of the AIA for more consequential and personal tasks might alter the perception of the AIA (Plangger and Montecchi 2020). With a longer-lasting and a closer relationship, the consumer will have more significant exposure, contact and interactions with the AIA. Consequently, in the long term, the consumers who have a close relationship with the AIA will be more aware of the AIA's mind and intelligence. This enhanced awareness could then amplify the positive effect of AIA anthropomorphism (i.e., perceiving a mind in the AIA) on a consumer's identity threat.

H5 The positive effect of AIA anthropomorphism on the perception of artificial intelligence's threat to human identity increases if the consumer's relationship with the AIA is closer and the relationship length is longer.

Empowering consumers in their relationships with artificial intelligence assistants

To provide a deeper exploration of AIA outcomes for consumers, we will lay out our reasoning for the relationship between the feeling of threat to human identity and consumer AI empowerment. We define AI empowerment as the consumers' perception of their own ability

to handle the decision-making processes that are related to the use of AIAs and the use of personal data collected by AIAs (Martin et al. 2017; Van Dyke et al. 2007). First, and extrapolating from our previous theorizing, we suggest that AIA's threat to human identity might disempower consumers in their relationship with the AIA, which then subsequently reduces consumer well-being. That is, we argue that identity threat creates an uncertainty in the human–AIA relationship about how to engage with the AIA. Such uncertainty, not knowing exactly the motives and intentions of the AIA, reduces consumers' ability to effectively deal with AIAs, that is, reducing consumer AI empowerment.

H6 Higher (vs. lower) threat to human identity decreases consumer well-being through reducing consumer AI empowerment.

Our preliminary studies and previous literature all suggest that consumers' awareness and knowledge of the data issues with their AIAs is astonishingly limited (e.g., Malkin et al. 2019). Thus, we examine three remedy strategies that aim to empower consumers in relation to the privacy of their personal data collected by AIAs. We propose that interventions that (1) raise consumers' awareness of data issues, (2) provide the consumers with solutions about how they can deal with data privacy issues and (3) encourage them to take action to protect the privacy of their data will enhance consumer AI empowerment.

In the adoption of innovations, research has shown something akin to a "honeymoon effect" where the novelty of the experience might initially be the main driving force of the attitude towards the AIA, initially shrouding relationship costs and benefits (Wells et al. 2010). But after extended exposure to the AIA, the consumers start to form a comprehensive, nuanced understanding of the relationship with the AIA and begin to think in terms of costs and benefits. The real relationship, so to speak, begins after the honeymoon and develops with time, when the AIA user experiences and responds to the pros and cons of the relationship. Therefore, we suggest that all three of our intervention strategies that we test in Study 2 (H7, H8 and H9) will be especially impactful for AIA users with a longer relationship length.

For the first strategy, we argue that an increased awareness of data issues in the relationship with AIA will help reduce the uncertainty about how to effectively deal with the AIA. We suggest that knowing more about the data issues in the relationship with AIA can attenuate the harmful effect of identity threat (induced by perceiving a mind in the AIA) on consumer AI empowerment, particularly for consumers with longer relationships with their AIA.

H7 Higher (vs. lower) consumer awareness for data issues in relationships with AIAs attenuates the harmful effect of AIA's threat to human identity by artificial intelligence on consumer AI empowerment, for consumers with longer (vs. shorter) relationship length.

On top of gaining awareness about the data issues, having knowledge of solutions on how to improve data security in relationships with AIAs can be beneficial to the consumer. Simply having an awareness of potential privacy threats might not be sufficient, and could even in some cases disempower the consumer (Olivero and Lunt 2004). By raising awareness about possible solutions, alongside the potential threats, firms might shift the power back to the consumer. Moreover, our preliminary study shows that consumers' knowledge of their privacy preferences and how to adjust them is surprisingly low. Raising consumers' awareness about potential solutions for data issues will further mitigate the uncertainty in the relationship with the AIA, reduce the cognitive cost of protective actions and provide a pathway to solutions. Therefore, we suggest that knowing more about how to deal with AIAs can attenuate the harmful effect of AIA's threat to human identity on consumer AI empowerment.

H8 Higher (vs. lower) consumer awareness about solutions on how to improve data security in relationships with AIAs attenuates the harmful effect of AIA's threat to human identity by artificial intelligence on consumer AI empowerment, for consumers with longer (vs. shorter) relationship length.

Besides learning about data issues or solutions, consumers may need to act and implement data security measures to strengthen their empowerment vis-à-vis the AIA. Going through privacy settings and making a specific decision carries a heavy cognitive load for consumers. It might

be necessary to give consumers some impetus to ensure that they do indeed take action. Explicitly requesting the consumers to change their privacy preferences to a specific setting pushes the consumers further towards taking action. With this extra push, the consumers will directly experience the results of taking action. This experience implicates competence, impact and self-efficacy, core elements of empowerment (Cattaneo and Chapman 2010). Therefore, we suggest that prompting the consumers to take action about their AIA privacy preferences can attenuate the harmful effect of identity threat on consumer AI empowerment.

H9 Taking action to improve data security in handling AIAs attenuates the harmful effect of AIA's threat to human identity on AI empowerment, for consumers with longer (vs. shorter) relationship length.

STUDY 1: AMBIVALENT EFFECTS OF AIA ANTHROPOMORPHISM ON USER–AIA RELATIONSHIPS

Procedure

In Study 1, we test H1, H2, H3, H4 and H5 and thus seek to elucidate the effect of AIA anthropomorphism on relationships between consumers and the AIA. For this purpose, we conducted an online consumer survey. The participants were 238 current AIA users who own a smart speaker in their homes (67% Amazon's Alexa, 26% Google's Google Assistant, 7% Apple's Siri). All of the participants were residents of the United Kingdom that were recruited through Prolific (M_{age}=37, 40% male, 60% female). Four hundred participants were invited to the survey and 389 participants completed this survey. The same participants were invited to a second survey after six months, where we measured additional constructs and key dependent variables. Having a time lag allowed us to reduce the common method variance (CMV), that is, the bias that might arise from consumer response tendencies if variables originate from the same data source (Alavi et al. 2018). There were 246 participants who completed both surveys, but 8 participants were excluded due to missing data and the final sample included 238 participants.

Measures

Main variables

We used established scales to operationalize the concepts in our model. The complete list of measurement items of main variables, scale reliabilities and the order of presentation are provided in Table 3 of the paper. We measured relationship length, overall satisfaction with the AIA (Garbarino and Johnson 1999), anthropomorphism of the AIA (Epley et al. 2008), trust felt towards the AIA (Leach et al. 2007), privacy concerns of the consumer related to their personal data (Smith et al. 1996), threat to human identity (Ferrari et al. 2016; Mende et al. 2019), consumer well-being (Bech et al. 2003) and relationship closeness (Castelo et al. 2019) with items from established scales adapted to our context. We measured the independent variables at time 1 and dependent variables at time 2. We introduced this time lag to reduce CMV issues and the likelihood of reversed causation (Alavi et al. 2018).

Control variables

We included a broad set of theoretically grounded control variables in the model estimation to reduce the likelihood of endogeneity issues due to omitted variable bias (Sande and Ghosh 2018) and to assess the stability of the hypothesized effects. First, we included perceived usefulness of the AIA and perceived ease of AIA use, both of which have been shown to play an important role in technology acceptance, use and trust (Davis 1989). We accounted for innovativeness of the consumer, because innovativeness is typically associated with greater intention to adopt a technology (Yi et al. 2006). We also included two demographics variables as controls, as both have been shown to play a role in tendency to anthropomorphize and engage with technology: age (Appel et al. 2020) and gender (Venkatesh et al. 2000). Finally, we added frequency of AIA use as a control because previous research suggests links of this variable with use and purchase behaviors with technology (Venkatesh and Agarwal 2006). A correlations table is provided in Table 4. The complete list of measurement items of control

variables, scale reliabilities and the order of presentation can be found in Table V in Appendix C. To examine the convergent and discriminant validity of all multi-item scales, we followed the standard procedures of estimating confirmatory factor analyses (Bagozzi et al. 1991). All scales conform to the prescribed values for the item reliabilities, composite reliability (CR) and average variance extracted (AVE) with one exception, which was slightly below the AVE threshold (AVE=.47 for Identity Threat). Moreover, the global fit statistics indicated a good fit of the measurement model (RMSEA=.049; TLI=.937; CFI=.945; SRMR=.054).

Model specification and results

To test whether the anthropomorphism of the AIA increases consumer satisfaction through elevated trust in the AIA (H1), increases privacy concerns (H2) and decreases consumer satisfaction (H3) and well-being (H4) through increasing threat to human identity by artificial intelligence, we specified a structural equation model as follows: we linked AIA anthropomorphism to trust and identity threat, then these two variables and all of our control variables to consumer privacy concerns, consumer satisfaction with the AIA and consumer well-being. As control paths, we also analyzed the direct links between trust and well-being, trust and privacy concerns, threat and satisfaction as well as the direct links from privacy concerns to consumer satisfaction and well-being. In addition, we analyzed the indirect and total effects of identity threat on privacy concerns, satisfaction and well-being of the consumer. We estimated this model using Stata 16 (StataCorp 2019), including 238 observations (Table 5).

Robustness checks

We conducted several robustness checks for which we report detailed results in Appendix A. First, in our study, we recruited only current AIA users. To alleviate concerns about a potential sample selection bias, we implemented Heckman selection correction (Heckman 1976). Our results remained stable after including the inverse Mills ratios in the model estimation. To

Table 3. List of measurement items and scale evaluations for main variables in the order of presentation.

Variables	Measurement Items	Scale Evaluations	
		Study 1	Study 2
Relationship Length	What is the approximate month and year in which you acquired (or received) [Platform]?	-	-
Consumer Satisfaction [Ω] (adapted from Garbarino and Johnson 1999)	How would you rate your overall satisfaction with [Platform]?	-	-
AIA Anthropomorphism [ϕ] (from Epley et al. 2008)	Please indicate how much you agree that [Platform] [γ] … • …has a mind of its own. • …has intentions. • …has free will. • …has consciousness. • …experiences emotions.	α =.86 CR=.87 AVE=.57	α =.90 CR=.91 AVE=.67
Trust in the AIA [ϕ] (adapted from Leach et al. 2007)	How much do you think the traits below describe [Platform]? • Honest • Sincere • Trustworthy	α =.92 CR=.91 AVE=.78	α =.87 CR=.87 AVE=.69
Privacy Concerns [ω] (adapted from Smith et al. 1996)	Please indicate how much you agree with the following statements. • I am worried that [Platform] collects personal data from me. • It scares me that [Platform] measures personal data of me. • I am worried that [Platform] will get personal information from me. • It is scary for me that [Platform] takes personal data from me.	α =.95 CR=.95 AVE=.84	α =.96 CR=.96 AVE=.87
Threat to Human Identity [ω] (adapted from Ferrari et al. 2016 & Mende et al. 2019)	Please indicate how much you agree with the following statements. • [Platform] seems to lessen the value of human existence. • I get the feeling that [Platform] could damage relations between people. • [Platform] could easily be used for evil (to fool, to harm, etc.) • [Platform] makes me worry about my place in the world.	α =.81 CR=.77 AVE=.47	α =.81 CR=.82 AVE=.53
Consumer Wellbeing [Ψ] (adapted from Bech et al. 2003)	Over the last two weeks… • I have felt cheerful and in good spirits. • I have felt calm and relaxed. • I have felt active and vigorous. • I woke up feeling fresh and rested. • My daily life has been filled with things that interest me.	α =.89 CR=.89 AVE=.62	α =.91 CR=.92 AVE=.69
Consumer AI Empowerment [ω] (adapted from Spreitzer 1995)	Please indicate how much you agree with the following statements. • I am confident about my ability to handle [Platform]. • I am self-assured about my capabilities to protect the privacy of my data that is collected by [Platform]. • I have mastered the skills to protect the privacy of my data that is collected by [Platform].	-	α =.88 CR=.88 AVE=.71
Relationship Closeness with the AIA [λ] (adapted from Castelo et al. 2019)	• Do you think the **Personal Organization** tasks (such as making calls, sending messages, scheduling, reminders, alarms, setting daily goals, etc.) that you perform with [Platform] are more consequential or inconsequential for you? • Do you think the tasks related to **getting Information** (such as searching information, listening to the news, asking the weather conditions, etc.) that you perform with [Platform] are more consequential or inconsequential for you? • Do you think the **Device Management** tasks (such as controlling smart home gadgets, lights, thermostats, security camera, etc.) that you perform with [Platform] are more consequential or inconsequential for you? • Do you think the **Purchase-related** tasks (such as searching for products to buy, asking price information or recommendations, renewing your subscription, ordering and tracking deliveries, etc.) that you perform with [Platform] are more consequential or inconsequential for you?	α =.80 CR=.80 AVE=.50	-

[ϕ] 7-point scale (1=Not at all, 7=Very much). [γ] [Platform] denotes Alexa, Google Assistant or Siri, according to each participant. [ω] 7-point scale (1=Strongly disagree, 7=Strongly agree). [Ω] 7-point scale (1=Not at all satisfied, 7= Completely satisfied). [Ψ] 6-point scale (1=At no time, 6= All of the time). [λ] 7-point scale (1=Inconsequential, 7=Consequential). α=Cronbach's alpha, AVE=Average variance extracted, CR= Composite reliability.
The measurement models show good global fit for Study 1 (RMSEA=.049; TLI=.937; CFI=.945; SRMR=.054) and Study 2 (RMSEA=.047; TLI=.942; CFI=.949; SRMR=.044).

Table 4. Correlations table, Study 1 and Study 2.

Variables, **Study 1**	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) AIA Anthropomorphism														
(2) Trust	.28													
(3) Identity Threat	.27	-.12												
(4) Privacy Concerns	-.08	-.27	.32											
(5) Satisfaction	.17	.44	-.12	-.28										
(6) Wellbeing	.06	.03	-.04	-.15	.11									
(7) Relationship Closeness	.06	.07	.12	-.08	.19	.04								
(8) Relationship Length	-.02	-.05	.11	.06	-.10	-.10	.02							
(9) Perc. Usefulness	.26	.34	.09	-.06	.49	.05	.23	.01						
(10) Perc. Ease of Use	.04	.28	-.12	-.07	.38	.02	.12	-.09	.27					
(11) Innovativeness	-.01	.25	-.06	-.10	.13	.05	.03	.11	.22	.40				
(12) Frequency of Use	.06	.17	.04	.06	.33	.05	.12	.03	.35	.19	.20			
(13) Age	.08	-.01	.01	-.09	-.09	-.01	-.05	-.06	-.14	-.22	-.14	.02		
(14) Gender	-.08	.02	-.11	-.03	-.03	.03	.03	-.02	.01	.02	.29	.12	.04	
M	2.19	4.83	3.00	4.75	5.30	3.43	4.22	2.12	4.47	5.69	4.85	2.87	37.1	-
SD	1.23	1.39	1.13	1.36	1.21	1.03	1.44	.97	1.29	.93	1.39	1.72	11.6	-

Variables, **Study 2**	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1) AIA Anthropomorphism																
(2) Trust	.24															
(3) Identity Threat	.44	-.07														
(4) Privacy Concerns	.20	-.22	.49													
(5) Satisfaction	.13	.45	-.15	-.21												
(6) Wellbeing	-.01	.09	-.14	-.13	.12											
(7) Empowerment	.04	.28	-.19	-.32	.29	.19										
(8) Relationship Length	-.05	-.02	-.04	-.04	-.01	-.07	.08									
(9) Perceived Usefulness	-.10	.36	-.06	-.12	.43	.12	.28	.02								
(10) Perceived Ease of Use	-.05	.20	-.19	-.17	.41	.11	.39	.09	.43							
(11) Innovativeness	-.01	.18	-.07	-.15	.19	.08	.37	.12	.31	.43						
(12) Frequency of AIA Use	.08$^{\gamma}$	.18	-.06	-.14	.30	.02	.19	.11	.31	.15	.29					
(13) Technology Attitude	.01	.39	-.26	-.29	.32	.13	.37	.02	.42	.35	.43	.21				
(14) Trust in Amazon	.7	.45	-.12	-.35	.38	.11	.32	-.04	.31	.21	.16	.18	.42			
(15) Age	-.06	-.05	-.02	-.03	.02	.01	-.08	.17	-.12	-.24	-.07	.07	-.08	.01		
(16) Gender	-.12	-.01	-.07	-.05	-.05	.10	.12	-.01	.08	.10	.37	.07	.17	-.01	-.01	
M	2.10	4.38	2.98	4.31	5.40	3.60	4.70	32.05	4.65	5.48	4.64	2.98	5.02	4.29	35.2	-
SD	1.22	1.32	1.22	1.55	1.06	1.12	1.21	15.00	1.26	1.10	1.54	1.60	1.02	1.46	12.9	-

Study 1 variables (top): |r|>=.17: *p<0.01*, |r|>=.13: *p<0.05*. *Study 2 variables (bottom)*: |r|>=.11: *p<0.01*, |r|>=.08: *p<0.05,* (except correlations marked with γ, which are not significant).
M= Mean, SD=Standard Deviation.

assess our model's accuracy and reliability, we bootstrapped the model, and the results remained stable (see Table 5). To rule out a common method bias, first we implemented Harman's single-factor test. We found that the total variance extracted by a single factor is 18%, which is well below the recommended threshold of 50% and suggests that common method variance (CMV) is not an issue in our study (Chang et al. 2010). Moreover, we also used the marker variable technique of Lindell and Whitney (2001) to address this issue further. When we ran the model using the adjusted correlation matrix, the statistical significances in our model remained stable. Therefore, we infer that common method bias is unlikely to influence Study 1. To account for potential endogeneity in our model estimation, we implemented the Durbin–Wu–Hausman tests (Hausman 1978). The results reject the hypothesis that the variables in our model are endogenous. To address this issue further, we also employed a two-step control function approach (e.g., Petrin and Train 2010) and our results remained stable.

Main indirect effects

For testing the formal hypotheses, we relied on the fully specified model including the full set of control variables. The results show that greater perceived anthropomorphism of the AIA increased the satisfaction of the consumer through increased trust in the AIA (b=.045, p<.01). This result supports H1 and successfully replicates the effects established by past literature. Furthermore, greater perceived anthropomorphism increased the privacy concerns of the consumers related to the use of their personal data through increasing the feeling of threat to human identity by artificial intelligence (b=.097, p<.001). This result fully supports H2 denoting harmful effects for consumers in relationship with AIAs. We did not find indirect effects of AIA anthropomorphism on consumer satisfaction and well-being through identity threat, therefore the hypotheses H3 and H4 were rejected. However, identity threat had significant negative indirect effects on consumer satisfaction (b=−.071, p<.01) and consumer

well-being (b=−.045, p<.05) through privacy concerns. Privacy concerns did have significant negative direct effects on consumer satisfaction (b=−.206, p<.001) and consumer well-being (b=−.152, p<.05). The full results are provided in Table 5, and further details can be found in Appendix C (Table VI).

Moderation effects

Next, we discuss the tests of the proposed moderators. All variables used in the interaction terms were mean centered. Relationship length or relationship closeness alone did not significantly moderate the effect of AIA anthropomorphism on AIA's threat to human identity. However, the three-way interaction between AIA's anthropomorphism, relationship length and relationship closeness had a positive moderating effect on the anthropomorphism to identity threat link (b=.130, p<.05). Those AIA users who have been using their AIA for a longer time and were closer to their AIA in their relationship exhibited even greater feelings of threat to their human identity by artificial intelligence (see interaction diagram in Figure 2). This result highlights the importance of user–AIA relationship characteristics and provides support for H5.

Discussion of Study 1

The results of Study 1 showed that perceived anthropomorphism of the AIA increased consumer satisfaction through increased trust in the AIA. This replication echoes the well-established literature showing the beneficial effects of anthropomorphism (e.g., Li and Sung 2021). Critically, in line with our theorizing, our results likewise demonstrate that there are psychological costs for the consumer in the relationship with the AIA, beyond the benefits. A greater perception of AIA's anthropomorphism significantly increased the privacy concerns of the consumer through increased identity threat. It is important to note that the harmful indirect effect of AIA's anthropomorphism on privacy concerns through identity threat was stronger than the beneficial indirect effect through trust. Moreover, this harmful effect of AIA

anthropomorphism was even more pronounced for consumers who had a longer and a closer relationship with the AIA. This result supports H5 and provides evidence about the potential costs and dangers of AIAs if a strong relationship forms between the user and the AIA.

Our hypotheses H3 and H4 were not supported as we found no indirect effects of AIA anthropomorphism on consumer satisfaction and well-being through identity threat. However, the results showed significant indirect effects of identity threat on both consumer satisfaction and well-being. Identity threat by the AIA reduced satisfaction and well-being through exacerbated privacy concerns, likewise pointing to potential harmful consequences for consumers in relationships with AIAs as well as indirectly for the company providing the service. That is, consumers' privacy concerns significantly reduced both consumer satisfaction and well-being (cf. Okazaki et al. 2020). This result illustrates the important downstream effects emerging from the anthropomorphism of the AIA that are relevant for both the consumers and marketing managers. The consumers in the digital age seem to be in part quite sensitive about the privacy of their personal data, even if they are not fully aware of how companies specifically deal with their data. With this series of results, we demonstrate that perceiving a mind in the AIAs might exacerbate the privacy concerns of the consumer and lead to unfavorable outcomes for both the consumers and the companies. Our results also point to the relevance of using a relationship lens to analyze consumer interaction with AIAs (cf. Steinhoff et al. 2019), that is, Study 1 provides nascent evidence that the harmful effects of AIAs become stronger as the relationship develops.

The harmful effects for consumers uncovered in Study 1 motivated us to take a closer look at the identity threat emerging from perceiving a mind in the AIA. Building on this finding, in Study 2 we explore strategies for consumers and companies to remedy this harmful effect.

STUDY 2: A FIELD EXPERIMENT TO TEST INTERVENTIONS THAT EMPOWER CONSUMERS

Procedure

In Study 2 we focus on the critical harmful path in the conceptual model and how to remedy the harmful effects for consumers. First, we seek to investigate whether identity threat reduces consumer AI empowerment (H6). Second, we examine the three intervention strategies proposed in H7, H8 and H9 to enhance consumers' empowerment in their relationship with AI. For this purpose, we designed a randomized field experiment with measures before and after the interventions. We invited 720 current Amazon smart speaker users to our study. All participants were residents of the United Kingdom recruited through Prolific and none of them participated in Study 1. Our field experimental design comprised four conditions: a control and three intervention conditions. While the control group simply completed a survey at times 1 and 2, the three intervention groups received an intervention directly after completing the first survey (see Appendix B for details of the interventions). In intervention group 1 we aimed to raise awareness about potentially problematic aspects of how Amazon handles consumer data. This group received information about two Alexa features related to data use and storage ("Saving Voice Recordings" and "Help Improve Alexa"), one paragraph of text each, describing their features and potentially problematic aspects. Intervention group 2 received the same information, and in addition, received a step-by-step illustration of how they could change their preferences related to the two Alexa features presented. Intervention group 3 received the same information as group 2, and, in addition, this group was explicitly asked to change their settings and keep using their AIA with the new settings for a week. The first request was to change the duration of storing voice recordings from the default setting "Save recordings until I delete them" to either "Save recordings for 3 months" or "Don't save recordings". This choice was given to avoid a reactance response in the participants. The

second request was to turn off the "Help Improve Alexa" feature which uses voice recordings to improve Alexa, which is by default turned on.

Consumers were allocated randomly to one of the four groups. After one week, the same group of 720 participants received an invitation for a second measurement. In our model estimation, we examined how the interventions in the first time point affect the measurements from the second time point to analyze the effects of the interventions. In both time points, we asked all participants to indicate current device settings. The final analysis sample consisted of 601 participants who completed both waves successfully (M_{age}=35.2, 57% female).

Measures

Main variables

As in Study 1, we used established scales to operationalize our concepts. Using the same measurements in Study 1, we asked the consumers when they purchased their Alexa-enabled device, their overall satisfaction with the AIA, their perceived anthropomorphism of the AIA, the trust they feel towards the AIA, their privacy concerns related to their personal data, threat to human identity and their well-being. In Study 2, additionally, we measured consumer AI empowerment with three items adapted from Spreitzer (1995). The list of measurement items and the order of presentation are provided in Table 3.

Control variables

We used the same six control variables as in Study 1. Moreover, we included two new controls in Study 2 to further account for additional influences. We measured the attitude of the AIA user towards technology, which is a key variable in the adoption, use and satisfaction of the technology users (Lin and Hsieh 2007). Second, we measured the trust towards Amazon. The trust towards the company has been shown to have a key role in ensuring consumer satisfaction (Morgan and Hunt 1994). A correlation table including descriptive statistics is provided in Table 4. The complete list of measurement items of control variables, scale reliabilities and the

order of presentation can be found in Table V in Appendix C. Measurement scales for both main and control variables conform to the prescribed values for the item reliabilities, CR and AVE. Moreover, the global fit statistics indicated a good fit of the measurement model (RMSEA=.047; TLI=.942; CFI=.949; SRMR=.044).

Manipulation check

As a manipulation check, we asked the participants a total of six questions at the time of second measurement to assess whether our interventions had the intended effect. The participants who received an intervention had greater awareness of privacy issues compared to the control group ($F(1,599) = 14.94$, $p<.001$). The participants who received information on how to protect their privacy (groups 2 & 3) had greater perceived knowledge of how to protect their privacy than those who did not receive such information ($F(1,599) = 25.96$, $p<.001$). Finally, the participants who were requested to take action (group 3) said they took action significantly more than those who did not receive a request ($F(1,599) = 50.19$, $p<.001$).

Model specification and results

To test whether identity threat reduces consumer well-being through reducing consumer AI empowerment (H6), we specified a structural equation model (SEM), linking identity threat to consumer AI empowerment, then linking empowerment to consumer well-being. To test the effectiveness of our interventions in reducing the effect of identity threat on empowerment (H7, H8, H9), we added relationship length and each of our interventions as moderators of the link between identity threat and empowerment. We dummy coded intervention groups to compare each intervention with the control group (Bagozzi and Yi 1989). As control paths, we included in the SEM all the paths we analyzed in Study 1. We estimated the model using Stata 16 (StataCorp 2019) including 601 observations (Table 5).

Robustness checks

To assess our model's accuracy and reliability, we bootstrapped the model and the results remain stable (see Table 5). To rule out a common method bias, we implemented Harman's single-factor test. We found that the total variance extracted by a single factor is 23%, which is below the recommended threshold of 50% and suggests that common method variance (CMV) is not an issue in our study (Chang et al. 2010). To account for potential endogeneity in our model estimation, we implemented the Durbin–Wu–Hausman tests (Hausman 1978). The results reject the hypothesis that the variables in our model are endogenous. Further information on all robustness checks is provided in the Appendix A.

Main indirect effects

First, the results of Study 2 replicated H1 and H2, showing that AIA's anthropomorphism increased the consumer satisfaction through increased trust in the AIA (b=.036, p<.001) and increased the privacy concerns of the consumer through increased threat to human identity (b=.214, p<.001). One of our key findings in Study 2 is that identity threat significantly reduced consumer well-being through reduced consumer AI empowerment (b=−.025, p<.05), providing support for our hypothesis H6. Analysis of non-hypothesized downstream effects of consumer AI empowerment showed that empowerment decreased consumers' privacy concerns (b=−.170, p<.001), but did not affect consumer satisfaction.

Moderation effects

Next, we discuss the tests of the proposed interactive effects of the intervention strategies. All non-dummy variables in the interaction terms were mean centered. As expected, the three-way interaction between identity threat, relationship length and the interventions resulted in the following significant effects. Raising consumers' awareness about data issues significantly reduced the negative effect of identity threat on consumer AI empowerment for consumers with longer relationship length (b=.118, p<.05). Raising awareness about potential solutions to data issues reduced the negative effect of identity threat on consumer AI empowerment for

consumers with longer relationship length, only at 10% significance level (b=.104, p<.10). Finally, requesting the consumers to take action about their privacy had the strongest moderating effect, significantly reducing the negative effect of identity threat on consumer AI empowerment for consumers with longer relationship length (b=.176, p<.01). These results provide support for our hypotheses H7, H8 and H9 with different degrees of significance. Our interventions, compared to a control condition, succeeded in attenuating the harmful effect of threat to human identity by artificial intelligence on consumer AI empowerment for consumers with longer relationship length. The interaction effects are depicted in Figure 2 and we interpret these findings further in the discussion section.

Interestingly, the two-way interaction between identity threat and relationship length had a significant negative effect on consumer AI empowerment (b=−.234, p<.05), meaning that identity threat due to AI decreased consumer AI empowerment particularly for consumers with longer relationships. These results provide additional support to the idea that harmful effects of AIA may become stronger as the consumer–AIA relationship develops. The full results are provided in Table 5, and further details can be found in Appendix C (Table VII).

Discussion of Study 2

The first key finding of Study 2 is that identity threat significantly reduced consumer well-being by diminishing consumer AI empowerment. This supports H6 and confirms Study 1 in that despite their many advantages, AI technologies may also be disempowering and harmful to consumers. Moreover, the negative effect of identity threat on consumer AI empowerment was significantly stronger for consumers with longer relationship length. This finding underlines the eligibility of adopting a relationship perspective on consumer-AIA exchanges and supports the idea that an extended exposure to the AIA is needed for the harmful effects to fully emerge.

We also found support for H7, H8 and H9, demonstrating the effectiveness of the intervention strategies to attenuate the harmful effect of identity threat on consumer AI empowerment for consumers with longer relationship length. In particular, prompting consumers to take action about their privacy in their relationship with the AIA had the most

Table 5. Results of Study 1 and Study 2.

Path		Full model	Model w/out controls	Full model, bootstrapped	95% CIs
Study 1					
Main links		*Coef. (SE)*	*Coef. (SE)*	*Coef. (SE)*	
Anthropomorphism [H1](ANTHRO)	**→Trust towards the AIA**	.236 (.068)***	.296 (.070)***	.209 (.058)***	[.094, .323]
Anthropomorphism [H2, H3, H4]	**→Threat to human identity**	.249 (.058)***	.252 (.056)***	.270 (.061)***	[.150, .391]
Trust towards the AIA	→Privacy Concerns	-.193 (.066)**	-.189 (.061)**	-.199 (.072)**	[-.340, -.058]
Threat to human identity [H2]	**→Privacy Concerns**	.387 (.076)***	.394 (.075)***	.325 (.067)***	[.194, .457]
Trust towards the AIA [H1]	**→Consumer Satisfaction**	.190 (.049)***	.329 (.053)***	.219 (.070)**	[.082, .356]
Threat to human identity [H3]	**→Consumer Satisfaction**	-.051 (.058)	-.040 (.068)	-.048 (.062)	[-.170, .074]
Trust towards the AIA	→Consumer Well-being	-.031 (.055)	-.007 (.051)	-.042 (.073)	[-.185, .101]
Threat to human identity [H4]	**→Consumer Well-being**	-.011 (.066)	-.008 (.065)	-.012 (.077)	[-.164, .139]
Privacy Concerns	→Consumer Satisfaction	-.184 (.047)***	-.147 (.055)**	-.206 (.053)***	[-.310, -.102]
Privacy Concerns	→Consumer Well-being	-.116 (.054)*	-.107 (.053)*	-.152 (.067)*	[-.285, -.020]
Main effects of the moderators & Interaction effects					
Relationship Closeness (RC)	→Threat to human identity	.086 (.048)	.077 (.048)	.110 (.063)	[-.014, .235]
Relationship Length (RL)	→Threat to human identity	.064 (.073)	.096 (.072)	.055 (.058)	[-.059, .168]
ANTHRO × RC	→Threat to human identity	-.025 (.038)	-.026 (.037)	-.041 (.062)	[-.163, .080]
ANTHRO × RL	→Threat to human identity	-.088 (.063)	-.077 (.063)	-.087 (.056)	[-.197, .124]
RC × RL	→Threat to human identity	.094 (.052)	.068 (.051)	.114 (.060)	[-.004, .231]
ANTHRO × RC X RL [H5]	**→Threat to human identity**	.087 (.041)*	.085 (.042)*	.130 (.059)*	[.015, .245]
ANTHRO × RC	→Trust towards the AIA	.016 (.044)	-.005 (.047)	.021 (.072)	[-.120, .163]
ANTHRO × RL	→Trust towards the AIA	.091 (.074)	.121 (.079)	.073 (.056)	[-.037, .183]
RC × RL	→Trust towards the AIA	-.030 (.061)	-.029 (.064)	-.030 (.068)	[-.163, .103]
ANTHRO × RC X RL	→Trust towards the AIA	-.065 (.049)	-.085 (.052)	-.080 (.061)	[-.200, .040]

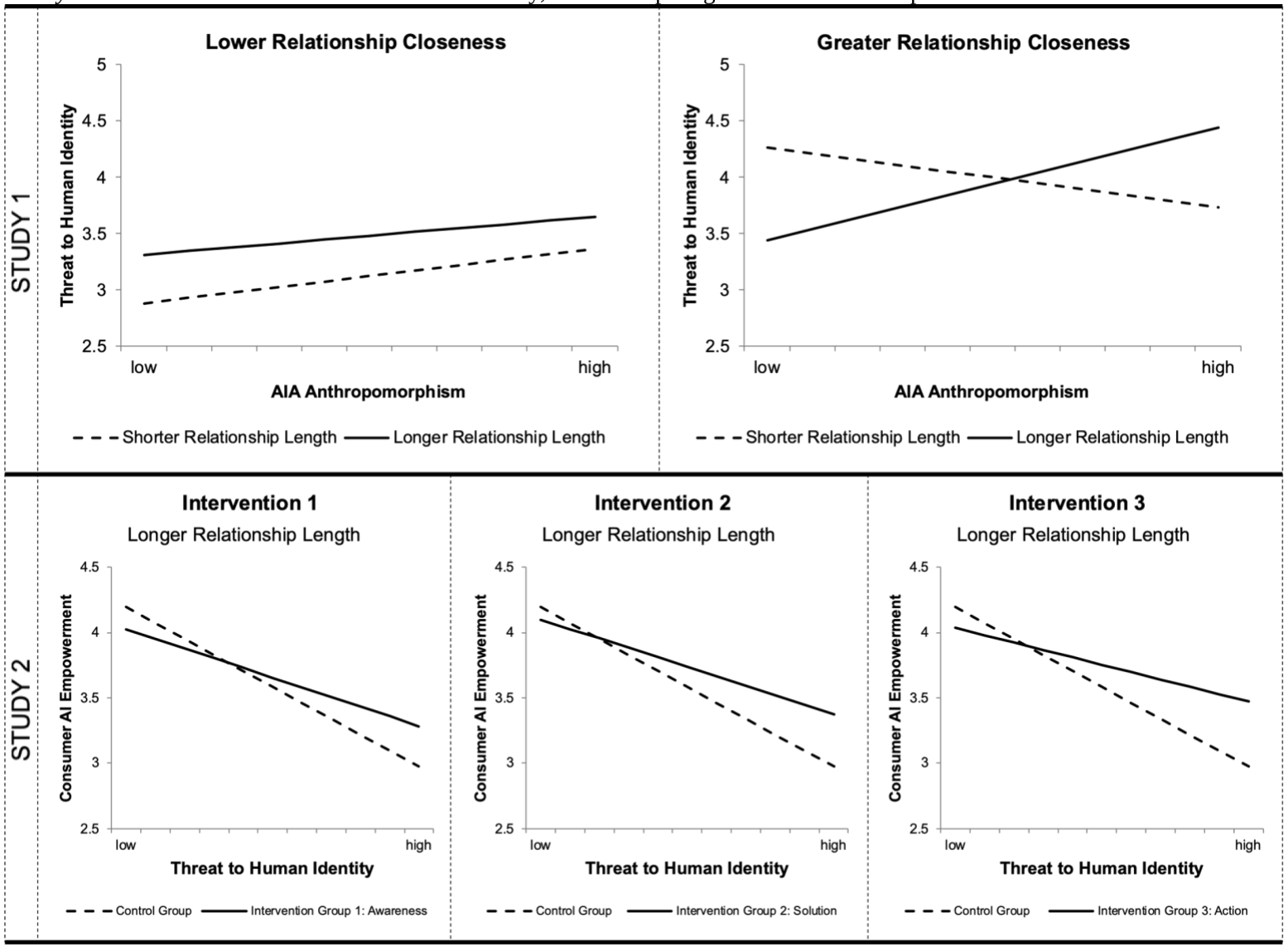
Full Model: R^2 for Satisfaction: .444; R^2 for Well-being: .031; R^2 for Privacy Concerns: .173 R^2 for Trust: .229; R^2 for Threat: .155.
Model without controls: R^2 for Satisfaction: .220; R^2 for Well-being: .022; R^2 for Privacy Concerns: .146 R^2 for Trust: .094; R^2 for Threat: .119.
Full Model, bootstrapped: R^2 for Satisfaction: .445; R^2 for Well-being: .031; R^2 for Privacy Concerns: .173 R^2 for Trust: .229; R^2 for Threat: .155.

Study 2					
Main links		*Coef. (SE)*	*Coef. (SE)*	*Coef. (SE)*	
Anthropomorphism	→Trust towards the AIA	.181 (.038)***	.259 (.042)***	.169 (.033)***	[.104, .234]
Anthropomorphism	→Threat to human identity	.445 (.036)***	.437 (.037)***	.445 (.037)***	[.373, .517]
Trust towards the AIA	→Consumer AI Empowerment	.067 (.038)	.225 (.037)***	.071 (.045)	[-.017, .160]
Threat to human identity [H6]	**→Consumer AI Empowerment**	-.195 (.073)**	-.304 (.080)***	-.195 (.074)**	[-.341, -.049]
Consumer AI Empowerment	→Privacy Concerns	-.216 (.049)***	-.268 (.046)***	-.170 (.041)***	[-.250, -.090]
Consumer AI Empowerment [H6]	**→Consumer Well-being**	.126 (.044)**	.142 (.040)***	.137 (.048)**	[.043, .231]
Consumer AI Empowerment	→Consumer Satisfaction	.030 (.033)	.135 (.034)***	.035 (.038)	[-.040, .111]
Privacy Concerns	→Consumer Well-being	-.016 (.036)	-.018 (.035)	-.022 (.055)	[-.129, .086]
Privacy Concerns	→Consumer Satisfaction	-.001 (.027)	-.024 (.029)	-.001 (.039)	[-.077, .077]
Trust towards the AIA	→Privacy Concerns	-.086 (.047)	-.183 (.043)***	-.072 (.042)	[-.156, .011]
Threat to human identity	→Privacy Concerns	.481 (.049)***	.518 (.049)***	.378 (.042)***	[.292, .465]
Trust towards the AIA	→Consumer Satisfaction	.197 (.031)***	.295 (.031)***	.244 (.039)***	[.168, .319]
Threat to human identity	→Consumer Satisfaction	-.072 (.035)*	-.106 (.038)**	-.083 (.038)*	[-.158, -.009]
Trust towards the AIA	→Consumer Well-being	.008 (.041)	.028 (.037)	.009 (.052)	[-.093, .112]
Threat to human identity	→Consumer Well-being	-.092 (.047)*	-.098 (.046)*	-.101 (.057)	[-.212, .011]
Main effects of the moderators & Interaction effects					
Relationship Length (RL)	→Consumer AI Empowerment	-.005 (.006)	-.002 (.006)	-.061 (.074)	[-.206, .084]
Intervention 1: Awareness (INT1)	→Consumer AI Empowerment	-.031 (.116)	-.054 (.028)	-.011 (.041)	[-.092, .070]
Intervention 2: Solution (INT2)	→Consumer AI Empowerment	.252 (.119)*	.216 (.131)	.089 (.042)*	[.007, .170]
Intervention 3: Action (INT3)	→Consumer AI Empowerment	.163 (.118)	.130 (.131)	.057 (.041)	[-.024, .138]
THREAT × RL	→Consumer AI Empowerment	-.015 (.005)**	-.014 (.006)*	-.234 (.095)*	[-.421, -.047]
THREAT × INT1	→Consumer AI Empowerment	.095 (.103)	.128 (.114)	.043 (.050)	[-.055, .140]
THREAT × INT2	→Consumer AI Empowerment	.130 (.097)	.159 (.106)	.069 (.056)	[-.041, .179]
THREAT × INT3	→Consumer AI Empowerment	.081 (.096)	.112 (.106)	.042 (.053)	[-.061, .146]
INT1 × RL	→Consumer AI Empowerment	.011 (.008)	.008 (.009)	.066 (.051)	[-.033, .166]
INT2 × RL	→Consumer AI Empowerment	.009 (.009)	.004 (.010)	.052 (.048)	[-.042, .146]
INT3 × RL	→Consumer AI Empowerment	.013 (.008)	.016 (.008)	.091 (.048)	[-.004, .186]
THREAT X RL X INT1 [H7]	**→Consumer AI Empowerment**	.017 (.007)*	.016 (.008)*	.118 (.054)*	[.011, .224]
THREAT X RL X INT2 [H8]	**→Consumer AI Empowerment**	.013 (.007)†	.016 (.008)*****	.104 (.061)†	[-.015, .223]
THREAT X RL X INT3 [H9]	**→Consumer AI Empowerment**	.018 (.006)**	.018 (.007)**	.176 (.066)**	[.046, .305]

Full Model: R^2 for Satisfaction: .404; R^2 for Well-being: .064; R^2 for Privacy Concerns: .369 R^2 for Trust: .313; R^2 for Threat: .284.
Model without controls: R^2 for Satisfaction: .232; R^2 for Well-being: .051; R^2 for Privacy Concerns: .306 R^2 for Trust: .058; R^2 for Threat: .191.
Full Model, bootstrapped: R^2 for Satisfaction: .404; R^2 for Well-being: .064; R^2 for Privacy Concerns: .369 R^2 for Trust: .313; R^2 for Threat: .284.

*p < 0.05, **p < 0.01, ***p < 0.001 (two-tailed); standardized coefficients, SE=standard error. Hypothesized parts are written in **bold**.
H1: supported. H2: supported. H3: only indirect support. H4: only indirect support. H5: supported. H6: supported. H7: supported. †H8: supported only at 10% sig. level. H9: supported.
More detailed results, including the results for control variables, are provided in Tables VI and VII in Appendix D.

Figure 2. *Study 1:* Interactive effect of AIA anthropomorphism, relationship closeness and relationship length on threat to human identity (top).
Study 2: Interactive effects of threat to human identity, relationship length and three field experiment interventions on consumer AI empowerment (bottom).



marked effect. When we asked for the consumers' current device settings, we found that 55% of the consumers in the third intervention did indeed choose to take action in response to our request and changed their preference for how long their voice recordings should be kept. This intervention not only alleviated the harmful effect of identity threat on consumer empowerment as we intended, but also resulted in real behavior change for many consumers. Moreover, 25% of the consumers in the second intervention group took action despite not being requested to make a change. This result emphasizes the importance of informed consumers who only need to know how to deal with their situation. Once they have a clear pathway to a solution, these consumers may take action without needing a further push. Finally, raising awareness about privacy issues of consumers with longer relationship length also psychologically empowers them, even if they do not take immediate action. The tangible changes in behavior and the resulting empowerment show that managers can empower the consumers by adequately informing them and encouraging them to take action in relation to their personal information.

GENERAL DISCUSSION

Theoretical contributions

This research investigates potential psychological costs and dangers of AIA anthropomorphism for consumers, and strategies to alleviate the revealed harmful effects. Two empirical studies provide convergent evidence expressing the effects of AIA anthropomorphism-induced identity threat on consumer empowerment and subsequently on consumer well-being. First, our results demonstrate that the harmful downstream effects of human identity threat may particularly be induced by an extended exposure to the AIA in the course of the relationship. With AI-powered technologies taking larger roles in our daily lives, our research highlights the need to account for this permanent ongoing nature of the consumer-AI relationship (cf. Huang and Rust 2021b; Kozinets and Gretzel 2021; Novak and Hoffman 2019). The AIA technology is unique in the sense that the interaction is ongoing from the waking to sleeping moments of

the consumer, in the consumer's home. Adopting a relationship perspective for studying AIA-user interactions is novel, because pertinent past research rather assumed a stimulus–response approach, in which the AIA functions as a stimulus to which consumers react immediately (e.g., Benlian et al. 2020; Li and Sung 2021). Therefore, we suggest that taking a relationship perspective is valuable in investigating AIAs, in addition to a stimulus–response model. Our first theoretical contribution to the literature on AIAs (e.g., Benlian et al. 2020; Foehr and Germelmann 2020; Li and Sung 2021) is that we can conceptualize user–AIA interactions as an ongoing exchange of benefits and psychological costs in a relationship, and the characteristics of this relationship play a crucial role in shaping our experience with AI. One implication is that future research should more intensively leverage theories of relationship development in marketing to examine user–AIA interactions (e.g., Dwyer et al. 1987). For instance, analogous to relationship marketing (Jap and Ganesan 2000), mapping out a user–AIA relationship lifecycle may be pertinent. An insightful question in this respect might be whether such relationship lifecycles are similar to conventional relationship lifecycles found in past research or exhibit AIA-specific idiosyncrasies.

Second, previous research has shown that perceiving a mind in a non-human entity engenders discrete effects, altering how the entity is perceived (e.g., in terms of its competence, agency, eeriness) (Mende et al. 2019; Waytz et al. 2014). We suggest that we can explain these scattered findings in the mind perception literature in a parsimonious way, i.e., with a costs–benefits approach. Specifically, we show that perceiving a mind in AIAs enables consumers to form a relationship with their AIA. People make inferences about the AIA's mind and these inferences shape the perceived benefits and costs of the relationship. That is, a perception of a mind in AIAs can be considered as a part of the benefits and costs of engaging with AI, just like other features (e.g., personalization, surveillance), collectively constituting an experiential relationship with AI. Therefore, it might be useful to approach any human–AI interaction as

potentially an exchange relationship whenever one perceives a mind in the AI, similar to one's own. Previous theories that attempted to explain the effects of mind perception, such as threat to distinctiveness (e.g., Ferrari et al. 2016) or psychological distance (e.g., Li and Sung 2021), could benefit from including a social exchange perspective in their attempts to understand mind perception in AI. Such an approach may provide a comprehensive understanding of mind perception in AI, which might have simultaneous contrasting effects on people, such as psychological closeness and threat to human identity (Ferrari et al. 2016; Li and Sung 2021).

Third, in recent marketing research, an intense discussion emerged on the consequences of AI for consumers and their experience (Cukier 2021; Kozinets and Gretzel 2021; Puntoni et al. 2021). In contrast to the extant literature showing benefits of AIA anthropomorphism (see Table 1), our research underlines that anthropomorphism in AIAs could induce psychological costs for consumers, manifested as a threat to their human identity. Anthropomorphism is being used increasingly in many AI-powered devices and it is necessary to enrich the current perspective in the literature (e.g., Blut et al. 2021). Our results provide clear support for this suggestion by differentiating a harmful dimension of AIA anthropomorphism. Thus, we contribute to past literature with a more balanced account of benefits and psychological costs of AI for consumers, as vehemently demanded in recent works (Cukier 2021; Puntoni et al. 2021). Seeing the ambivalent effects generated by AIAs on consumers, we suggest that it is important to leverage theories related to psychological costs to understand this aspect of AIAs in more detail, such as techno-stress (Ayyagari et al. 2011) or psychological strain (Edwards 1996). Established theories of anthropomorphism (e.g., Epley et al. 2007) could be meaningfully extended by including in their framework the psychological costs, as well as benefits, generated in interactions of humans with anthropomorphized AI entities.

Fourth, importantly, this finding also shows that the fear of being replaced by AI is not just a matter of being replaced in one's job; most people actually buy AIAs to be voluntarily

replaced in menial tasks. Being replaced, in fact, implies something more profound: it is about an AI with a rivaling mind being in a "psychological competition" with humans, which questions our human nature and role in a digital world. While previous research has conceptualized human identity threat as a fear of being replaced and distant dystopian tales of robot dominance over humans (e.g., Ferrari et al. 2016), we show that there is also an immediate psychological threat arising from perceiving a competing mind in the AI. To the best of our knowledge, we are the first to propose this feeling of threat to human identity as a driver of consumers' privacy concerns. Past research has identified intrusive capabilities of AI-powered devices (e.g., data exploitation, extensive surveillance) as drivers of privacy concerns (Maedche et al. 2019; Müller 2021), but not their nature as "intelligent machines with a rivaling mind". This finding points to a deeper fear of humans in relation to their privacy, beyond the more proximal sources of concern such as data security or extensive surveillance. Therefore, established theories on technology acceptance such as the technology acceptance model (Davis et al. 1989) should integrate in their framework the psychological costs elicited by mind perception, especially since nowadays most technology is powered by AI.

Managerial implications

Our results show that managers face a difficult dilemma in the marketing of AIAs: if managers endow AIAs with anthropomorphic features, it entails ambivalent effects, such that consumers are more satisfied with the AIA, but at the same time, experience less general well-being. Our findings thus provide managers with a starting point to optimize outcomes from AIAs such that they profit from beneficial effects and avoid harmful consequences. Therefore, our first recommendation to managers is to endow AIAs with anthropomorphism only if consumers are well-informed about the privacy of their data and are confident in taking action to protect their privacy in the relationship with the AIA. Certainly, there are individual differences in consumers' tendency to anthropomorphize, and some people do not anthropomorphize their

AIAs at all. However, for some others, if the perception of a virtual intelligent mind triggers a relationship, firms might elicit human–AI relationships that are richer than a few archetypal relationship styles (e.g., master–servant) (Novak and Hoffman 2019), and as rich as the human experience (e.g., metaverses). There could be great promise in employing anthropomorphism in AI prudently, but an indiscriminate use may undermine the potential of cutting-edge AI technologies for both consumers and firms (cf. De Ruyter et al. 2018; Grewal et al. 2020).

Our second recommendation to the managers is that, in an attempt to minimize the harmful effects of AIA anthropomorphism, they should try to empower consumers regarding the protection of their personal data. We present three practical ways to empower users for handling their data privacy: (1) informing consumers about the data practices of the firm, (2) informing consumers about ways to protect their data privacy and (3) encouraging consumers to take action to protect the privacy of their data. These ways of empowering users go beyond what is traditionally done online. Firms currently must ask their customers for their consent for data use, and some firms ask the customers their preferences but given the lack of customer knowledge on digital data and privacy, this typically is no more than a formality. An innovative way could be to use the AIAs' conversational ability to transmit such information to users seamlessly, by integrating privacy dialogs into user interactions. Firms might see such practices as unwanted extra costs, however, it could turn into substantial benefits for the firm for two reasons.

The first reason why firms might want to empower consumers is that AIAs as a purchase channel have certainly not been exploited to their full potential. While 32% of users searched for products and product reviews, only 9% of users made purchases through AIAs. Despite being aware of the convenience of making a purchase just with a voice command, many consumers avoid it partly because of the uncertainty of the integrity of their personal data (Stucke and Ezrachi 2018). Alleviating data privacy concerns and improving well-being of the

consumers could reinforce better consumer relationships and increase purchase through this unique channel.

Second, consumers oftentimes believe that a firm's data practice is an indication of how they will be treated as a customer (Cisco 2019). We have seen disastrous examples of careless management of consumer data privacy, such as Facebook, which has seen its reputation plummet over the past few years (Axios Harris Poll 100, 2021). This shows that firms' current disclosure practices may be insufficient and emphasizes the need to push beyond disclosing rudimentary information to consumers (Martin and Palmatier 2020). Based on the results of our field experiment, we recommend creating and efficiently communicating transparent privacy policies, improving the salience and accessibility of privacy preferences and encouraging the consumers to take action to protect their privacy. A conscientious and transparent manner of managing consumer data will not only shield the company from continuous government scrutiny and potential legal expenses, but is also a corporate digital responsibility (Lobschat et al. 2021; Martin and Murphy 2017). A consumer-centric data relationship management (e.g., Krafft et al. 2017; McKinsey 2021) may be ideal and effective for building mutually beneficial and lucrative relationships with well-informed consumers (Bleier et al. 2020; Plangger and Montecchi 2020).

Limitations

Our study is not without limitations. We included AIA users of all brands in Study 1, but we targeted only Amazon Alexa users in Study 2. This was a necessary limitation for our field experimental design to preserve homogeneity in our sample. Different platforms have a different set of security settings, presented at different levels of ease of accessibility. We would have liked to include all platforms in Study 2, but the results across intervention groups would not have been entirely comparable. While we added a control variable in our model for

company specific perceptions in Study 2, future research could best clarify potentially different consumer attitudes to different brands by investigating consumers of all AIA providers.

While our research carries implications for most AI-powered devices in which consumers might perceive a mind, our empirical work focuses specifically on AIAs that are embedded in smart speakers that are used at home (e.g., an Amazon Echo device). The extent to which our results might be generalizable for other AI-powered entities can best be revealed through further research. Also, despite seeing a clear behavior change in AIA users as documented by changed privacy preferences, we do not have data to confirm a prolonged effect. Future research could investigate the extent to which such behavior changes in AIA users persist over time.

Our study has limitations in relation to the measurement of satisfaction and identity threat. Considering the practical advantages such as higher response rates and due to the high number of variables in our study, we have opted for an established single-item measurement of satisfaction (Garbarino and Johnson 1999). While previous research found them to be comparable, future research could use multi-item measures as well as single-item measures to enhance the robustness of the findings (cf. Gardner et al. 1998). Finally, future research could use more detailed identity threat measurements, considering potential sub-dimensions of identity threat (e.g., real vs. symbolic threat) to explore this phenomenon with more granularity.

Directions for Future Research

Based on our findings, we raise potential research questions for future research on relationship marketing, consumer empowerment and privacy management as well as mind perception in AI (see Table 6). First, we recommend future research to likewise adopt a relationship perspective on exchanges of consumers and AI and explore this relational exchange with longitudinal models. Indeed, digital platforms such as AIAs might have tremendous untapped potential as a medium for establishing and maintaining customer relationships. Therefore, investigating the

development of a relationship over time and exploring relationship trajectories will provide a whole new way of looking at AIAs, as something more than a convenience gadget that collects a lot of personal data. Exploring the relationships between the consumers and the AI-powered platforms may unveil versatile interactions that go beyond purchase and foster consumer loyalty (e.g., Wichmann et al. 2022). The relationships that consumers form with intermediary platforms such as Alexa may gradually replace the traditional consumer–firm relationships, by acting as a firm's new access point to consumers. In particular, employing the user log files, longitudinally available and stored by AIAs, which track purchases, AIA tasks, changes of data/privacy settings, and exchanges between AIA and consumer could provide an intriguing opportunity for groundbreaking, longitudinal marketing research in this direction.

Second, to empower AIA users, our interventions aimed at informing and encouraging users regarding the protection of their personal data in relationships with AIAs. This is certainly not the only way to empower consumers, but arguably one of the easiest ways. Future research could explore additional strategies, potentially even more effective at making the consumers feel empowered and alleviate their privacy concerns. However, managers should consider that empowerment strategies may introduce more friction into a consumer experience, because consumers become more engaged in the process. In a digital world where frictionless or seamless experience has become a major priority, future research could investigate the trade-offs in consumer experience that empowerment strategies may require (e.g., having to read information, as in our interventions). Potentially, AIAs could use their natural interaction capabilities to avoid this issue by integrating conversational privacy dialogs into user interactions, therefore not sacrificing seamless consumer experience completely. Delivering privacy notices and choices through a two-way verbal dialogue between the users and AIAs could provide the users with a more natural, seamless and effective interface for controlling their privacy. Such an intuitive way of communicating privacy preferences will reduce notice

Table 6. Future research questions.

Research Area/ Field	Key Result	Managerial Implications	Future Research Questions
Relationship Marketing	• User-AIA interactions can be characterized as an ongoing, dynamic relationship. The characteristics of this relationship play a crucial role in shaping our experience with AI.	• AIAs might have some untapped potential as a medium to develop customer relationships.	• How does the consumers' relationship with AIAs develop over time? • How do consumers migrate from one stage of the relationship or the other? Are there critical events that shape the relationship trajectories? • How do consumer sentiments change over time and how can they inform other consumer metrics (e.g., purchase)? • How can AIAs be used effectively to establish and maintain strong customer relationships, as an intermediary between the customer and the firm? • How do the relationship dynamics start and evolve when there are multiple users of one single device?
Consumer Empowerment & Privacy management	• Informing consumers about the data practices of AIAs, about ways to protect their data privacy and encouraging them to take action to protect their data privacy empowers them and subsequently improves their well-being. • Empowering the consumers in relation to the privacy of the personal data alleviates their privacy concerns.	• Actively informing and encouraging the consumers about protecting their data could improve the relationships and increase sales through the AIA • Managing consumer privacy effectively can be an opportunity to enhance the brand image and create a competitive advantage for the firms.	• How can we empower consumers, other than by decreasing the information asymmetry or by encouraging them to take action? • How can the information best be delivered to the consumers? • What can an empowered consumer mean for a company? • How will the public perception of a company change when it prioritizes the privacy of consumer data? • How can a company turn effective consumer privacy management into a competitive advantage? • Empowerment may involve a consumer experience that is less seamless, because consumers are more engaged in a process. What are potential trade-offs for a firm that consumer empowerment requires?
Mind perception/ Anthropomorphism in AI	• Users perceive a mind in their AIAs, and this constitutes both a benefit and a cost. • The perception of a mind in the AIA constitutes a psychological cost for the user, manifested as a threat to human identity.	• Marketers should use anthropomorphism in technology prudently and consider potential, still unexplored consequences.	• How do different consumer segments respond differently to anthropomorphism in AIAs? • Are there individual characteristics that condition the costs and benefits of anthropomorphism in AI? • Do consumers perceive a mind in other AI-powered devices and form relationships with them? • What kind of implications does perceiving a rivaling mind in AI carry for the future? • How might the context of use influence the costs and benefits of anthropomorphism in AI? (e.g., use of AI in education vs. service contexts) • Which particular anthropomorphic features could lead to greater mind perceptions? (e.g., interactivity, learning, personality, embodiment, speech).

complexity and fatigue, which is a major problem with current privacy policies and settings. Firms can thus potentially rejuvenate their relationships with their customers, especially those with a defeatist attitude towards their privacy, which may be leading them to actively avoid further engagement with their AIAs.

Third, anthropomorphic features of AIAs seem to play an intriguing central role in this technology. A fine-grained perspective is required on which particular anthropomorphic features could lead to greater mind perceptions and how they might differ in the effects they elicit (e.g., interactivity, learning, personality, embodiment, speech) (Rijsdijk et al. 2007). Thus, it would be a worthwhile endeavor for future research to develop a taxonomy of anthropomorphic features and assess their differential effects. Moreover, AIAs represent a new, unique purchasing channel, despite not being exploited to their full potential yet. Future research should investigate the effects of AIA anthropomorphism on novel, untested consumer outcomes such as willingness to pay for a product, purchase likelihood and the overall perception of the provider company.

Finally, regarding potentially harmful effects of AIAs, consumers' experienced identity threat related to AI assumes a quintessential role. This is noteworthy, because many people in society have concerns over whether AI will gradually displace humans not just in mechanical tasks, but also in tasks that require thinking and feeling (Huang and Rust 2018). We focus on AIAs which have so far replaced us mostly in menial tasks. Yet, all kinds of digital technologies now encircle us in our daily lives, replacing us in increasingly complex tasks. A broader fear of being replaced by AI in tasks that we think as exclusively human could drastically change the public attitude towards technology and innovation (Davenport et al. 2020). The point is not to be a storm crow, but to encourage future research to thoroughly examine our relationship with AI in a wider context. We believe that investigating the nomological network (antecedents, mechanisms, outcomes, remedy strategies) of consumers' relationships with

AIAs and privacy concerns should assume a key role on the research agenda in the digital age. Both researchers and policymakers should consider implications of AI for consumers whose human identity might be threatened, but also for the future economy that is already being transformed by AI.

Declaration of conflicting interests

The authors declare that they have no conflicts of interest.

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APPENDICES

APPENDIX A

Additional Robustness Checks

Harman Single-Factor Test

Harman's single factor-test is a common test carried out by researchers to examine common method variance (CMV) issues in their studies. This analysis is a procedure that is conducted after data collection to check whether a single latent factor is accountable for the variance in the data (Chang et al. 2010). In this method, we loaded all items from every construct to a factor analysis to check whether one single latent factor emerges or whether a single latent factor accounts for the majority of the covariance among the measures. The generated principle component analysis output revealed 16 distinct factors with eigenvalues greater than 0.5 accounting for 85% of the total variance. The first unrotated factor captured only around 18% of the variance in the data. Neither of the underlying assumptions were met; no single factor emerged and the first factor did not capture most of the variance. These results suggest that CMV is not a major issue in Study 1. Similarly, in Study 2, we followed the same procedure and the generated principle component analysis output revealed 15 distinct factors with eigenvalues greater than 0.5 accounting for 83% of the total variance. The first unrotated factor captured only around 23% of the variance in the data. Neither of the underlying assumptions were met; no single factor emerged and the first factor did not capture most of the variance. These results suggest that CMV is neither a major issue in Study 2.

Lindell & Whitney test

To further investigate a potential common method bias in Study 1, we used the marker variable technique by Lindell and Whitney (2001). We corrected the correlations for common method variance using the correlation between a marker variable that is theoretically unrelated to the variables in the model. We ensured a high reliability of the marker variable by including a multi-item scale with a Cronbach's alpha value of .87. As a marker variable we chose anxiety

in social situations measured with four items (e.g., “I often feel nervous in casual get-togethers.”, 7-point Likert scale anchored “Strongly disagree” and “Strongly agree”). The lowest positive correlation between social anxiety and our constructs is .01, which we used to adjust all correlations in our dataset following the technique outlined by Lindell and Whitney (2001). We then ran the model using the adjusted correlation matrix. Since the statistical significances in our model remained stable, we infer that common method bias is unlikely to influence Study 1 (Homburg et al. 2010).

Durbin-Wu-Hausman test

To account for potential endogeneity in our model estimations in both studies, we have implemented the Durbin-Wu-Hausman test (Hausman 1978). We ran the test on the path from AIA anthropomorphism to identity threat, anthropomorphism is the variable with potential suspicion of being endogenous. The test of endogeneity for AIA anthropomorphism in Study 1 resulted in the retaining the null hypothesis that the variable is exogenous (Durbin *chi2* = 3.3583, *p*=.0669; Wu-Hausman $F(1,223)=3.19168$, *p*= .0754). The test of endogeneity for AIA anthropomorphism in Study 2 also resulted in the retaining the null hypothesis that the variable is exogenous (Durbin *chi2* = .011, *p*=.915; Wu-Hausman $F(1,592)=.011$, *p*= .916).

Control Function Approach

To further account for potential endogeneity in our model estimation in Study 1, we resort to an established standard approach to correct for potential endogenous influences on the predictors (Sande and Ghosh 2018). In line with recent research, we employ a two-step control function approach (e.g., Petrin and Train 2010). In the first stage, AIA anthropomorphism is regressed on a set of predictors of AIA anthropomorphism including an instrument which is excluded in the main model estimation. The first stage produces an endogeneity correction term (residual of the first stage equation) which we then include as an additional predictor in the main model estimation.

In the first stage, AIA anthropomorphism is regressed on a set of predictors of AIA anthropomorphism including an instrument which is excluded in the main model estimation (see result table of the first stage in Table I). That is, we regress AIA anthropomorphism on age, gender, ease of AIA use, innovativeness of the AIA user, frequency of AIA use, loneliness of the AIA user and the platform used by the AIA user, as these variables may influence the extent to which consumers perceive an artificial mind in an AIA. The exact AIA platform used, whether user adopted Alexa, Siri, Bixby, or Google Assistant, serves as the excluded instrument. That is, Google Assistant is coded as 0 (zero) and Alexa, Siri, and Bixby as 1 (one). This variable should be correlated with AIA anthropomorphism as Alexa etc. may exhibit more humanlike features, conforming to the relevance criterion. Yet, the exact platform used should not inherently be related to customers' identity threat, conforming to the exclusion criterion. Table I below displays the results of the first stage estimations.

In the second stage, we have included the residual of the first stage equation as a control in the model estimation. This procedure accounts for potential endogeneity of the AIA anthropomorphism predictor. The results remain stable for all hypothesized paths (except the main effect of AIA anthropomorphism on trust, the replication hypothesis H_1) while correcting for the potential endogeneity of AIA anthropomorphism with this analysis (for the model estimations of second stage, see Table I).

Heckman Selection Correction

Since we use a sample of current AIA users in our Study 1, we wanted to make sure that a potential sample selection bias does not distort our results. To this end, we implemented Heckman selection correction (Heckman 1976). In the selection equation, we included privacy concerns to account for potential selection effects due to this variable, among a diverse set of predictor which differentiate AIA users from non-users. In the instrument selection, we used a dataset of 100 non-users that was collected as a part of the preliminary consumer survey. The

instrument we chose in the first stage probit regression was household size. Household size conforms to the relevance and exclusion restrictions necessary for an effective instrument in the selection equation. That is, household size should increase the likelihood of owning an AIA seeing that families are more prone to buy and employ the diverse smart home functions of AIA, while household size should not inherently affect trust or identity threat. Thus, it should conform to the relevance and exclusion restriction. Household size appears in the first stage, influencing the probability of an observation appearing in the sample, but do not influence our dependent variables of interest in the second stage model, thus meeting both relevance and exclusion criteria. The inverse Mills ratio was generated from the estimation of the probit model in the first stage and then was included in the model estimation in the second stage. All our results remained stable in the ensuing model estimation. The results of this analysis indicate that sample selection issues do not unduly distort our findings. Table II below displays the results of both stages of the analysis.

Table I. Results of the control function approach to address endogeneity issues in the model estimation of Study 1.

Path		Coefficient (SE)	95% Confidence Intervals
First Stage – Finding an endogeneity term			
Age	→Anthropomorphism	.010 (.007)	[-.003, .024]
Gender	→Anthropomorphism	-.223 (.169)	[-.556, .110]
Ease of AIA use	→Anthropomorphism	.043 (.096)	[-.148, .234]
Innovativeness	→Anthropomorphism	.000 (.066)	[-.132, .131]
Frequency of AIA use	→Anthropomorphism	.046 (.047)	[-.047, .140]
Relationship closeness (RC)	→Anthropomorphism	.059 (.055)	[-.050, .167]
Relationship length (RL)	→Anthropomorphism	-.037 (.082)	[-.201, .125]
Loneliness	→Anthropomorphism	.083 (.040)*	[.005, .162]
Platform used †	→Anthropomorphism	.461 (.178)**	[.110, .814]
Second Stage – Main model estimation			
Anthropomorphism	→Trust	-.382 (.253)	[-.878, .114]
ANTHRO X RC		.003 (.037)	[-.070, .075]
ANTHRO X RL		.155 (.062)*	[.034, .277]
RC X RL		-.068 (.051)	[-.168, .031]
ANTHRO X RC X RL		-.012 (.041)	[-.092, .067]
Correction instrument		.546 (.258)*	[.041, 1.051]
Anthropomorphism	→Threat to Human Identity	.707 (.255)**	[.206, 1.208]
ANTHRO X RC		-.030 (.037)	[-.103, .044]
ANTHRO X RL		-.087 (.063)	[-.210, .036]
RC X RL		.099 (.051)	[-.001, .200]
ANTHRO X RC X RL		.088 (.041)*	[.007, .169]
Correction instrument		-.478 (.260)	[-.988, .032]
Trust	→Privacy Concerns	-.117 (.078)	[-.271, .036]
Threat to Human Identity		.409 (.078)***	[.256, .561]
Anthropomorphism		-.201 (.301)	[-.791, .389]
Correction instrument		.061 (.305)	[-.537, .659]
Privacy Concerns	→Consumer Satisfaction	-.207 (.048)***	[-.302, -.112]
Trust		.066 (.058)	[-.048, .181]
Threat to Human Identity		-.072 (.061)	[-.191, .048]
Anthropomorphism		.150 (.226)	[-.294, .594]
Correction instrument		-.108 (.230)	[-.559, .342]
Privacy Concerns	→Consumer Well-being	-.112 (.052)*	[-.215, -.010]
Trust		-.009 (.063)	[-.133, .115]
Threat to Human Identity		.013 (.066)	[-.117, .142]
Anthropomorphism		-.590 (.243)*	[-1.065, -.114]
Correction instrument		.656 (.246)**	[.175, 1.138]
Log likelihood at convergence	-7172.1254		
Number of observations	238		

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$ (two-tailed); SE=standard error. † Endogeneity correction term used in main model estimation.

Table II: Results of the Heckman selection correction analysis to address a potential sample selection bias in the results of Study 1.

Path		Coefficient (SE)	95% Confidence Intervals
First Step – Selection Model			
Age	→Owning an AIA	.015 (.006)*	[.003, .028]
Gender	→Owning an AIA	-.264 (.141)	[-.540, .012]
Household Size †	→Owning an AIA	.315 (.154)*	[.013, .618]
Education	→Owning an AIA	.037 (.046)	[-.053, .126]
Innovativeness	→Owning an AIA	.354 (.050)***	[.256, .452]
Privacy Concerns	→Owning an AIA	-.166 (.055)**	[-.274, -.059]
General Data Concerns	→Owning an AIA	.096 (.070)	[-.042, .233]
Second Stage – Main model estimation including inverse Mills ratios (IMR)			
Anthropomorphism (ANTHRO)	→Trust towards the AIA	.231 (.068)***	[.098, .364]
Relationship Closeness (RC)		-.010 (.056)	[-.120, .100]
Relationship Length (RL)		-.032 (.085)	[-.196, .135]
ANTHRO X RC		.016 (.044)	[-.069, .102]
ANTHRO X RL		.089 (.073)	[-.055, .232]
RC X RL		-.040 (.060)	[-.158, .078]
ANTHRO X RC X RL		-.069 (.048)	[-.164, .025]
Age		-.002 (.008)	[-.019, .014]
Gender		.101 (.181)	[-.254, .456]
Perceived Usefulness		.210 (.072)**	[.068, .352]
Perceived Ease of Use		.239 (.100)*	[.043, .434]
Innovativeness		-.091 (.121)	[-.328, .145]
Frequency of Use		.021 (.050)	[-.077, .119]
Inverse Mills ratio		-1.982 (.855)*	[-3.658, -.306]
Anthropomorphism (ANTHRO)	→Threat to Human Identity	.255 (.057)***	[.143, .368]
Relationship Closeness (RC)		.087 (.048)	[-.006, .180]
Relationship Length (RL)		.066 (.072)	[-.075, .206]
ANTHRO X RC		-.026 (.037)	[-.098, .047]
ANTHRO X RL		-.085 (.062)	[-.207, .036]
RC X RL		.104 (.051)*	[.005, .204]
ANTHRO X RC X RL		.091 (.041)*	[.011, .171]
Age		.008 (.007)	[-.006, .022]
Gender		-.393 (.153)**	[-.694, -.092]
Perceived Usefulness		.028 (.061)	[-.092, .149]
Perceived Ease of Use		-.203 (.084)*	[-.368, -.037]
Innovativeness		.277 (.102)**	[.077, .477]
Frequency of Use		.031 (.042)	[-.052, .115]
Inverse Mills ratio		2.166 (.724)**	[.747, 3.584]
Trust in the AIA	→Privacy Concerns	-.141 (.059)*	[-.257, -.025]
Threat to Human Identity		.307 (.068)***	[.173, .441]
Age		.020 (.008)**	[.005, .035]
Gender		-.397 (.164)*	[-.718, -.075]
Perceived Usefulness		-.005 (.064)	[-.131, .122]
Perceived Ease of Use		.060 (.089)	[-.113, .234]
Innovativeness		.635 (.109)***	[.422, .848]
Frequency of Use		.067 (.045)	[-.021, .155]
Anthropomorphism		-.087 (.065)	[-.214, .041]
Inverse Mills ratio		6.197 (.788)***	[4.652, 7.742]
Trust in the AIA	→Consumer Satisfaction	.190 (.049)***	[.094, .287]
Threat to Human Identity		-.051 (.058)	[-.166, .063]
Privacy Concerns		-.191 (.053)***	[-.296, -.087]
Age		-.003 (.006)	[-.015, .009]
Gender		-.105 (.136)	[-.373, .162]
Perceived Usefulness		.283 (.053)***	[.179, .387]
Perceived Ease of Use		.303 (.073)***	[.160, .446]
Innovativeness		-.099 (.095)	[-.286, .088]
Frequency of Use		.136 (.037)***	[.063, .209]
Anthropomorphism		.008 (.054)	[-.097, .114]
Inverse Mills ratio		.213 (.727)	[-1.212, 1.639]
Trust in the AIA	→Consumer Well-being	-.029 (.055)	[-.138, .079]
Threat to Human Identity		-.011 (.066)	[-.141, .118]
Privacy Concerns		-.146 (.060)*	[-.264, -.029]
Age		.002 (.007)	[-.012, .016]
Gender		-.015 (.154)	[-.316, .287]
Perceived Usefulness		.015 (.060)	[-.102, .132]
Perceived Ease of Use		-.001 (.082)	[-.162, .160]
Innovativeness		.116 (.108)	[-.095, .327]
Frequency of Use		.033 (.042)	[-.049, .115]
Anthropomorphism		.048 (.060)	[-.070, .167]
Inverse Mills ratio		.902 (.819)	[-.704, 2.508]

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$ (two-tailed); SE=standard error. † Chosen instrument in the first stage probit regression.

APPENDIX B

Intervention Texts

Following are the full texts of the interventions used in the field experiments in Study 2. All three intervention groups received the following information. Intervention groups 2 and 3 also received step-by-step illustrations of how to change these settings. Intervention group 3, in addition to the information and the illustration, was explicitly asked to change their settings and keep using their device with the selected settings.

---*VOICE RECORDINGS* When you speak to Alexa, a recording of what you asked Alexa is sent to Amazon's cloud, where Amazon processes your request and other information. To detect and respond to voice commands, the speakers' microphones have to continuously listen for their wake word (e.g., "Alexa"). However, multiple mishaps have been reported with Alexa mishearing wake words and smart speakers' 'always listening' capabilities have been the focus of much public debate. By default, Amazon stores your recorded voice interactions on the cloud and does not delete them. Amazon uses your voice recordings or transcripts to analyze your data, behavior and preferences, and may target you with personalized ads and recommendations on its different platforms.

---*HELP IMPROVE ALEXA* When "Help Improve Alexa" feature is turned on, your device sends information back to the company to help improve Alexa. Amazon uses your requests to Alexa to train their speech recognition and natural language understanding systems. Amazon employees may review a small sample of your requests manually by listening and coding your voice recordings. The practice of manually reviewing voice recordings has prompted consumers to question how exactly the collected information is being used and who has access to it. Moreover, Amazon may share your voice recordings and transcripts with third-party applications and service providers.

APPENDIX C

Additional Tables and Figures

Table III: Descriptive statistics for all variables that entered the SEMs in the Study 1 and Study 2.

Variable	Mean	SD	Variance	Skewness	Kurtosis
Study 1 (N=238)					
Anthropomorphism	2.19	1.23	1.52	.96	3.07
Trust	4.83	1.39	1.94	-.65	3.38
Threat	3.00	1.13	1.28	.31	2.62
Privacy Concerns	4.75	1.36	1.84	-.47	3.02
Consumer Wellbeing	3.43	1.03	1.06	.05	2.21
Consumer Satisfaction	5.30	1.21	1.46	-1.06	4.46
Relationship Closeness	3.82	1.25	1.57	-.60	2.68
Relationship Length (year)	2.11	.97	.94	.98	3.93
Perceived Usefulness	4.47	1.29	1.67	-.93	3.47
Perceived Ease of Use	5.68	.93	.86	-.51	3.07
Innovativeness	4.85	1.39	1.92	-.40	2.38
Frequency of AIA Use	2.87	1.72	2.97	1.11	3.54
Age	37.1	11.6	133.74	.65	3.15
Study 2 (N=601)					
Anthropomorphism	2.10	1.22	1.48	1.16	3.78
Trust	4.37	1.31	1.73	-.39	2.97
Threat	2.98	1.22	1.49	.39	2.67
Privacy Concerns	4.31	1.54	2.39	-.36	2.28
Consumer Wellbeing	3.60	1.12	1.26	-.29	2.23
Consumer Satisfaction	5.40	1.06	1.13	-.86	4.16
Consumer AI Empowerment	4.70	1.21	1.46	-.43	2.74
Relationship Length (month)	32.05	14.98	224.52	.62	3.62
Perceived Usefulness	4.65	1.26	1.59	-.64	3.17
Perceived Ease of Use	5.48	1.10	1.20	-.90	3.92
Innovativeness	4.64	1.52	2.37	-.42	2.25
Frequency of AIA Use	2.98	1.60	2.56	.98	3.41
Age	35.2	12.9	166.53	.73	2.91
Attitude towards Technology	5.02	1.02	1.04	-.34	3.02
Trust in Amazon	4.29	1.46	2.13	-.43	2.56

Table IV: Details of the participants in the preliminary study.

Interviewee Code	Gender	Age	Income (in thousands per year, USD equivalent)	Family Status	Occupation	Education	Relationship Length with AIA (years)	Length of Interview
A	F	27	< 10	single	Business Development	Master Degree	2.5	29:15
B	M	21	< 10	single	Student	Higher School Degree	1.5	38:45
C	F	56	20 - 30	married	Teacher	School Degree	2	43:25
D	F	41	> 60	married	Professor	Ph.D.	3	38:26
E	M	27	40 - 50	single	Brand Manager	Master Degree	1	41:13
F	F	23	30 - 40	single	Bank clerk	Higher School Degree	6	20:40
G	F	39	10 - 20	married	Hair stylist	School Degree	2	16:20
H	F	52	N/A	married	Tax advisor	Higher School Degree	1	21:00
I	F	51	<10	married	Office worker	School Degree	2	23:33
J	F	32	> 70	married	Product management	Ph.D.	0.5	45:45
L	F	28	40-50	single	Researcher	Ph.D.	3	18:07

Table V. List of measurement items for control variables in the order of presentation.

Variables	Measurement Items	Cronbach's Alpha	
		Study 1	Study 2
Frequency of AIA Use	How often do you use [Platform]$^{\gamma}$?	-	-
Perceived Usefulness of the AIA $^{\omega}$ (adapted from Davis 1989)	Please indicate how much you agree with the following statements. • Using [Platform] for accomplishing tasks increases my productivity. • Using [Platform] improves my performance at accomplishing tasks. • Using [Platform] enhances my effectiveness at accomplishing tasks. • Using [Platform] enables me to accomplish tasks more quickly.	α=.96 CR=.95 AVE=.83	α=.94 CR=.94 AVE=.80
Perceived Ease of AIA Use $^{\omega}$ (adapted from Davis 1989)	Please indicate how much you agree with the following statements. • Learning to use [Platform] is easy for me. • I find it easy to get [Platform] to do what I want it to do. • I find [Platform] to be easy to use.	α=.87 CR=.88 AVE=.71	α=.90 CR=.90 AVE=.76
Innovativeness of the AIA User $^{\omega}$ (adapted from Parasuraman 2000)	Please indicate how much you agree with the following statements. • In general, I am among the first in my circle of friends to acquire new technology when it appears. • I keep up with the latest technological developments in my areas of interest. • I enjoy the challenge of figuring out high-tech gadgets. • I find that I have fewer problems than other people in making technology work for me.	α=.90 CR=.90 AVE=.70	α=.91 CR=.91 AVE=.72
Attitude towards Technology $^{\omega}$ (adapted from Parasuraman 2000)	Please indicate how much you agree with the following statements. • Technology gives people more control over their daily lives. • Technology is always to the benefit of humans. • I think big developments in technology will bring about more good in the world. • I trust technology.	-	α=.81 CR=.83 AVE=.55
Trust in Amazon $^{\omega}$ (adapted from Martin et al. 2016)	Regarding Amazon's customer data activities, I think… • I trust Amazon. • I have confidence in Amazon's behaviors. • Amazon is reliable.	-	α =.92 CR=.92 AVE=.80

$^{\gamma}$ [Platform] denotes the name of the SPA that each participant uses (Alexa, Google Assistant or Siri). $^{\omega}$ 7-point scale (1=Strongly disagree, 7=Strongly agree). α=Cronbach's alpha, CR= Composite reliability, AVE=Average variance extracted.

Table VI. Detailed Results of Study 1.

Path		Full model	Model w/out controls	Full model, bootstrapped	95% CIs
Main links		*Coef. (SE)*	*Coef. (SE)*	*Coef. (SE)*	
Anthropomorphism H1(ANTHRO)	**→Trust towards the AIA**	.236 (.068)***	.296 (.070)***	.209 (.058)***	[.094, .323]
Anthropomorphism H2, H3, H4	**→Threat to human identity**	.249 (.058)***	.252 (.056)***	.270 (.061)***	[.150, .391]
Trust towards the AIA	→Privacy Concerns	-.193 (.066)**	-.189 (.061)**	-.199 (.072)**	[-.340, -.058]
Threat to human identity H2	**→Privacy Concerns**	.387 (.076)***	.394 (.075)***	.325 (.067)***	[.194, .457]
Trust towards the AIA H1	**→Consumer Satisfaction**	.190 (.049)***	.329 (.053)***	.219 (.070)**	[.082, .356]
Threat to human identity H3	**→Consumer Satisfaction**	-.051 (.058)	-.040 (.068)	-.048 (.062)	[-.170, .074]
Trust towards the AIA	→Consumer Well-being	-.031 (.055)	-.007 (.051)	-.042 (.073)	[-.185, .101]
Threat to human identity H4	**→Consumer Well-being**	-.011 (.066)	-.008 (.065)	-.012 (.077)	[-.164, .139]
Privacy Concerns	→Consumer Satisfaction	-.184 (.047)***	-.147 (.055)**	-.206 (.053)***	[-.310, -.102]
Privacy Concerns	→Consumer Well-being	-.116 (.054)*	-.107 (.053)*	-.152 (.067)*	[-.285, -.020]
Main effects of the moderators					
Relationship Closeness (RC)	→Threat to human identity	.086 (.048)	.077 (.048)	.110 (.063)	[-.014, .235]
Relationship Length (RL)	→Threat to human identity	.064 (.073)	.096 (.072)	.055 (.058)	[-.059, .168]
Interaction effects					
ANTHRO × RC	→Threat to human identity	-.025 (.038)	-.026 (.037)	-.041 (.062)	[-.163, .080]
ANTHRO × RL	→Threat to human identity	-.088 (.063)	-.077 (.063)	-.087 (.056)	[-.197, .124]
RC × RL	→Threat to human identity	.094 (.052)	.068 (.051)	.114 (.060)	[-.004, .231]
ANTHRO × RC X RL H5	**→Threat to human identity**	.087 (.041)*	.085 (.042)*	.130 (.059)*	[.015, .245]
ANTHRO × RC	→Trust towards the AIA	.016 (.044)	-.005 (.047)	.021 (.072)	[-.120, .163]
ANTHRO × RL	→Trust towards the AIA	.091 (.074)	.121 (.079)	.073 (.056)	[-.037, .183]
RC × RL	→Trust towards the AIA	-.030 (.061)	-.029 (.064)	-.030 (.068)	[-.163, .103]
ANTHRO × RC X RL	→Trust towards the AIA	-.065 (.049)	-.085 (.052)	-.080 (.061)	[-.200, .040]
Control Paths					
Age	→Trust towards the AIA	.008 (.007)		.068 (.061)	[-.052, .188]
Gender		-.039 (.173)		-.014 (.061)	[-.132, .106]
Perceived Usefulness		.224 (.073)**		.208 (.074)**	[.064, .353]
Perceived Ease of Use		.255 (.101)*		.170 (.076)*	[.022, .319]
Innovativeness		.140 (.069)*		.139 (.074)	[-.005, .284]
Frequency of Use		.013 (.051)		.016 (.062)	[-.105, .138]
Age	→Threat to human identity	-.004 (.006)		-.037 (.065)	[-.165, .091]
Gender		-.240 (.147)		-.104 (.066)	[-.234, .026]
Perceived Usefulness		.013 (.062)		.015 (.088)	[-.156, .187]
Perceived Ease of Use		-.220 (.086)**		-.181 (.070)**	[-.319, -.043]
Innovativeness		.024 (.058)		.030 (.078)	[-.123, .182]
Frequency of Use		.040 (.043)		.061 (.070)	[-.076, .197]
Age	→Privacy Concerns	-.012 (.007)		-.103 (.054)	[-.208, .002]
Gender		.051 (.173)		.018 (.062)	[-.104, .141]
Perceived Usefulness		-.040 (.072)		-.039 (.063)	[-.162, .084]
Perceived Ease of Use		.034 (.099)		.023 (.065)	[-.104, .150]
Innovativeness		-.076 (.067)		-.078 (.070)	[-.215, .059]
Frequency of Use		.092 (.050)		.117 (.066)	[-.012, .247]
Anthropomorphism		-.107 (.073)		-.097 (.064)	[-.222, .027]
Age	→Consumer Satisfaction	-.004 (.005)		-.039 (.052)	[-.141, .064]
Gender		-.090 (.126)		-.037 (.051)	[-.136, .062]
Perceived Usefulness		.282 (.053)***		.303 (.061)***	[.183, .422]
Perceived Ease of Use		.301 (.073)***		.233 (.070)***	[.095, .370]
Innovativeness		-.123 (.049)*		-.142 (.062)*	[-.263, -.020]
Frequency of Use		.136 (.037)***		.194 (.044)***	[.109, .280]
Anthropomorphism		.008 (.054)		.009 (.052)	[-.093, .111]
Age	→Consumer Well-being	-.002 (.006)		-.021 (.071)	[-.160, .118]
Gender		.049 (.143)		.023 (.068)	[-.109, .156]
Perceived Usefulness		.011 (.060)		.014 (.074)	[-.131, .158]
Perceived Ease of Use		-.006 (.082)		-.005 (.076)	[-.154, .143]
Innovativeness		.015 (.056)		.020 (.073)	[-.123, .163]
Frequency of Use		.034 (.042)		.057 (.076)	[-.091, .205]
Anthropomorphism		.048 (.061)		.058 (.074)	[-.088, .203]
Model fit					
CFI / SRMR / RMSEA		.928/.027/.064	.816/.050/.082	.928/.027/.064	

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$ (two-tailed); standardized coefficients, SE=standard error. Hypothesized parts are written in **bold**.

Table VII. Detailed Results of Study 2.

Path		Full model	Model: No controls	Full model, bootstrapped	95% CIs
Main links		*Coef. (SE)*	*Coef. (SE)*	*Coef. (SE)*	
Anthropomorphism	→Trust towards the AIA	.181 (.038)***	.259 (.042)***	.169 (.033)***	[.104, .234]
Anthropomorphism	→Threat to human identity	.445 (.036)***	.437 (.037)***	.445 (.037)***	[.373, .517]
Trust towards the AIA	→Consumer AI Empowerment	.067 (.038)	.225 (.037)***	.071 (.045)	[-.017, .160]
Threat to human identity H6	**→Consumer AI Empowerment**	-.195 (.073)**	-.304 (.080)***	-.195 (.074)**	[-.341, -.049]
Consumer AI Empowerment	→Privacy Concerns	-.216 (.049)***	-.268 (.046)***	-.170 (.041)***	[-.250, -.090]
Consumer AI Empowerment H6	**→Consumer Well-being**	.126 (.044)**	.142 (.040)***	.137 (.048)**	[.043, .231]
Consumer AI Empowerment	→Consumer Satisfaction	.030 (.033)	.135 (.034)***	.035 (.038)	[-.040, .111]
Privacy Concerns	→Consumer Well-being	-.016 (.036)	-.018 (.035)	-.022 (.055)	[-.129, .086]
Privacy Concerns	→Consumer Satisfaction	-.001 (.027)	-.024 (.029)	-.001 (.039)	[-.077, .077]
Trust towards the AIA	→Privacy Concerns	-.086 (.047)	-.183 (.043)***	-.072 (.042)	[-.156, .011]
Threat to human identity	→Privacy Concerns	.481 (.049)***	.518 (.049)***	.378 (.042)***	[.292, .465]
Trust towards the AIA	→Consumer Satisfaction	.197 (.031)***	.295 (.031)***	.244 (.039)***	[.168, .319]
Threat to human identity	→Consumer Satisfaction	-.072 (.035)*	-.106 (.038)**	-.083 (.038)*	[-.158, -.009]
Trust towards the AIA	→Consumer Well-being	.008 (.041)	.028 (.037)	.009 (.052)	[-.093, .112]
Threat to human identity	→Consumer Well-being	-.092 (.047)*	-.098 (.046)*	-.101 (.057)	[-.212, .011]
Main effects of the moderators & Interaction effects					
Relationship Length (RL)	→Consumer AI Empowerment	-.005 (.006)	-.002 (.006)	-.061 (.074)	[-.206, .084]
Intervention 1: Awareness (INT1)	→Consumer AI Empowerment	-.031 (.116)	-.054 (.028)	-.011 (.041)	[-.092, .070]
Intervention 2: Solution (INT2)	→Consumer AI Empowerment	.252 (.119)*	.216 (.131)	.089 (.042)*	[.007, .170]
Intervention 3: Action (INT3)	→Consumer AI Empowerment	.163 (.118)	.130 (.131)	.057 (.041)	[-.024, .138]
THREAT × RL	→Consumer AI Empowerment	-.015 (.005)**	-.014 (.006)*	-.234 (.095)*	[-.421, -.047]
THREAT × INT1	→Consumer AI Empowerment	.095 (.103)	.128 (.114)	.043 (.050)	[-.055, .140]
THREAT × INT2	→Consumer AI Empowerment	.130 (.097)	.159 (.106)	.069 (.056)	[-.041, .179]
THREAT × INT3	→Consumer AI Empowerment	.081 (.096)	.112 (.106)	.042 (.053)	[-.061, .146]
INT1 × RL	→Consumer AI Empowerment	.011 (.008)	.008 (.009)	.066 (.051)	[-.033, .166]
INT2 × RL	→Consumer AI Empowerment	.009 (.009)	.004 (.010)	.052 (.048)	[-.042, .146]
INT3 × RL	→Consumer AI Empowerment	.013 (.008)	.016 (.008)	.091 (.048)	[-.004, .186]
THREAT X RL X INT1 H7	**→Consumer AI Empowerment**	.017 (.007)*	.016 (.008)*	.118 (.054)*	[.011, .224]
THREAT X RL X INT2 H8	**→Consumer AI Empowerment**	.013 (.007)†	.016 (.008)*	.104 (.061)†	[-.015, .223]
THREAT X RL X INT3 H9	**→Consumer AI Empowerment**	.018 (.006)**	.018 (.007)**	.176 (.066)**	[.046, .305]
Control Paths					
Age	→Trust towards the AIA	-.001 (.004)		-.009 (.040)	[-.087, .070]
Gender		-.087 (.097)		-.033 (.037)	[-.106, .040]
Perceived Usefulness		.168 (.043)***		.159 (.044)***	[.072, .246]
Perceived Ease of Use		.002 (.049)		.002 (.042)	[-.081, .085]
Innovativeness		.001 (.037)		.001 (.045)	[-.088, .090]
Frequency of Use		.023 (.030)		.028 (.038)	[-.047, .103]
Attitude towards technology		.264 (.055)***		.206 (.039)***	[.129, .282]
Trust towards Amazon		.253 (.035)***		.282 (.039)***	[.205, .359]
Age	→Threat to human identity	-.002 (.003)		-.020 (.033)	[-.085, .045]
Gender		-.007 (.092)		-.003 (.039)	[-.080, .074]
Perceived Usefulness		.066 (.041)		.068 (.046)	[-.022, .158]
Perceived Ease of Use		-.146 (.047)**		-.131 (.045)**	[-.219, -.044]
Innovativeness		.072 (.035)*		.091 (.048)	[-.003, .184]
Frequency of Use		-.047 (.029)		-.062 (.038)	[-.137, .013]
Attitude towards technology		-.277 (.052)***		-.231 (.046)***	[-.320, -.141]
Trust towards Amazon		-.081 (.033)*		-.096 (.040)*	[-.175, -.018]
Age	→Privacy Concerns	-.002 (.004)		-.019 (.034)	[-.086, .047]
Gender		.038 (.110)		.012 (.037)	[-.060, .085]
Perceived Usefulness		.053 (.049)		.043 (.046)	[-.047, .133]
Perceived Ease of Use		.048 (.058)		.034 (.041)	[-.047, .114]
Innovativeness		-.024 (.043)		-.023 (.045)	[-.111, .064]
Frequency of Use		-.038 (.034)		-.039 (.039)	[-.115, .038]
Attitude towards technology		-.016 (.065)		-.010 (.047)	[-.103, .082]
Trust towards Amazon		-.261 (.042)***		-.245 (.043)	[-.330, -.160]
Anthropomorphism		.133 (.049)**		.105 (.039)**	[.028, .181]
Age	→Consumer Satisfaction	.008 (.003)**		.104 (.035)**	[.036, .171]
Gender		-.149 (.073)*		-.070 (.032)*	[-.133, -.008]
Perceived Usefulness		.138 (.033)***		.164 (.038)***	[.090, .239]
Perceived Ease of Use		.274 (.038)***		.285 (.044)***	[.198, .372]
Innovativeness		-.051 (.028)		-.075 (.046)	[-.165, .016]
Frequency of Use		.097 (.023)***		.148 (.033)***	[.083, .219]
Attitude towards technology		-.007 (.043)		-.007 (.042)	[-.087, .076]
Trust towards Amazon		.081 (.027)**		.111 (.042)**	[.030, .193]
Anthropomorphism		.059 (.033)		.069 (.034)*	[.001, .136]
Age	→Consumer Well-being	.002 (.004)		.026 (.042)	[-.056, .109]
Gender		.188 (.097)		.083 (.053)*	[-.001, .167]
Perceived Usefulness		.052 (.044)		.059 (.049)	[-.038, .155]
Perceived Ease of Use		.018 (.051)		.018 (.050)	[-.080, .116]
Innovativeness		-.025 (.038)		-.034 (.053)	[-.138, .070]
Frequency of Use		-.028 (.030)		-.041 (.046)	[-.130, .049]
Attitude towards technology		.022 (.057)		.020 (.051)	[-.080, .119]
Trust towards Amazon		.017 (.038)		.022 (.050)	[-.076, .120]
Anthropomorphism		.029 (.043)		.032 (.051)	[-.067, .131]
Model fit					
CFI / SRMR / RMSEA		.607/.037/.128	.429/.061/.133	.607/.037/.128	

*p < 0.05, **p < 0.01, ***p < 0.001, †p<.10 (two-tailed); standardized coefficients, SE=standard error. Hypothesized parts are written in **bold**.

Figure I. Main research model in light of previous literature.

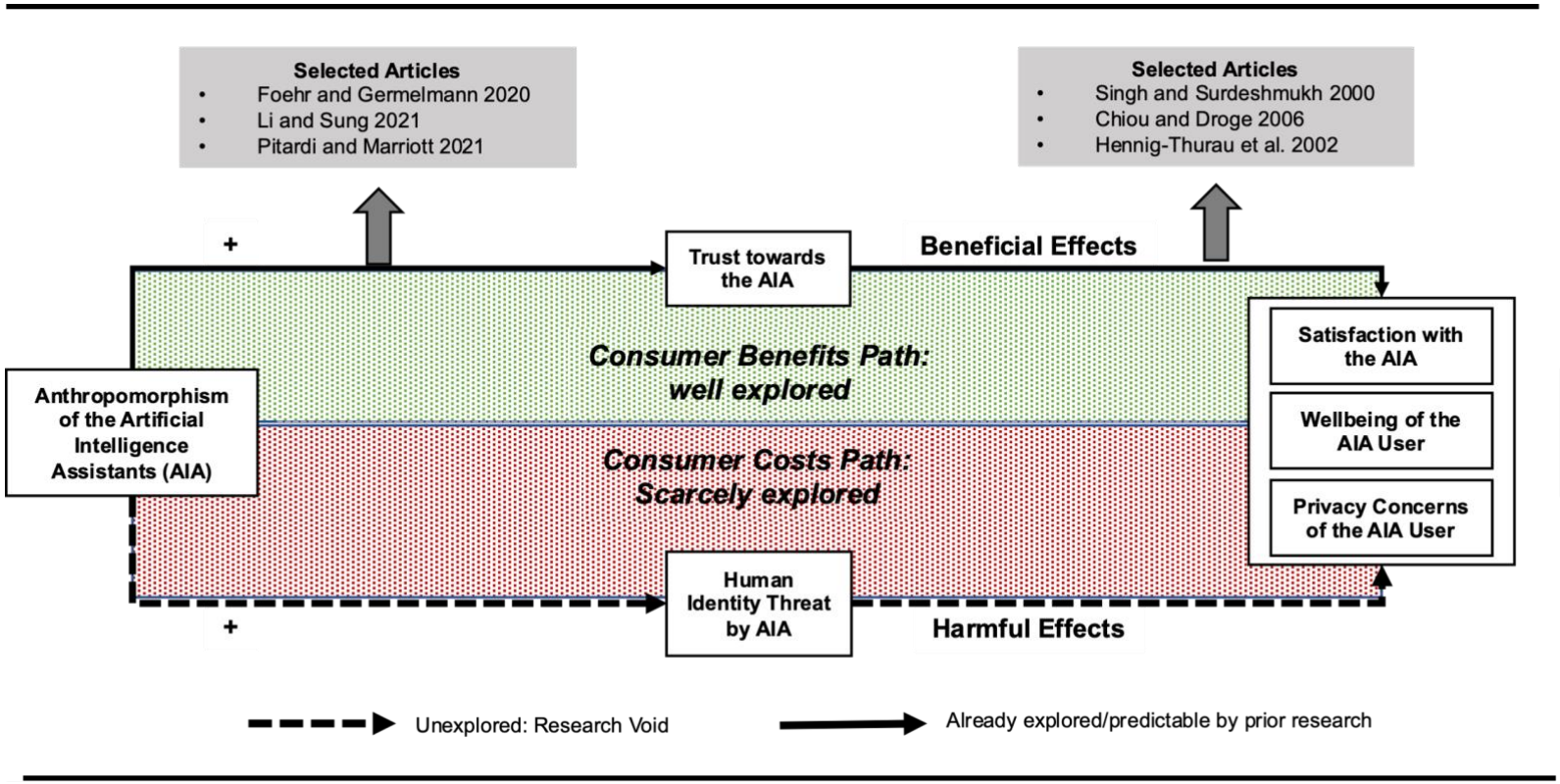
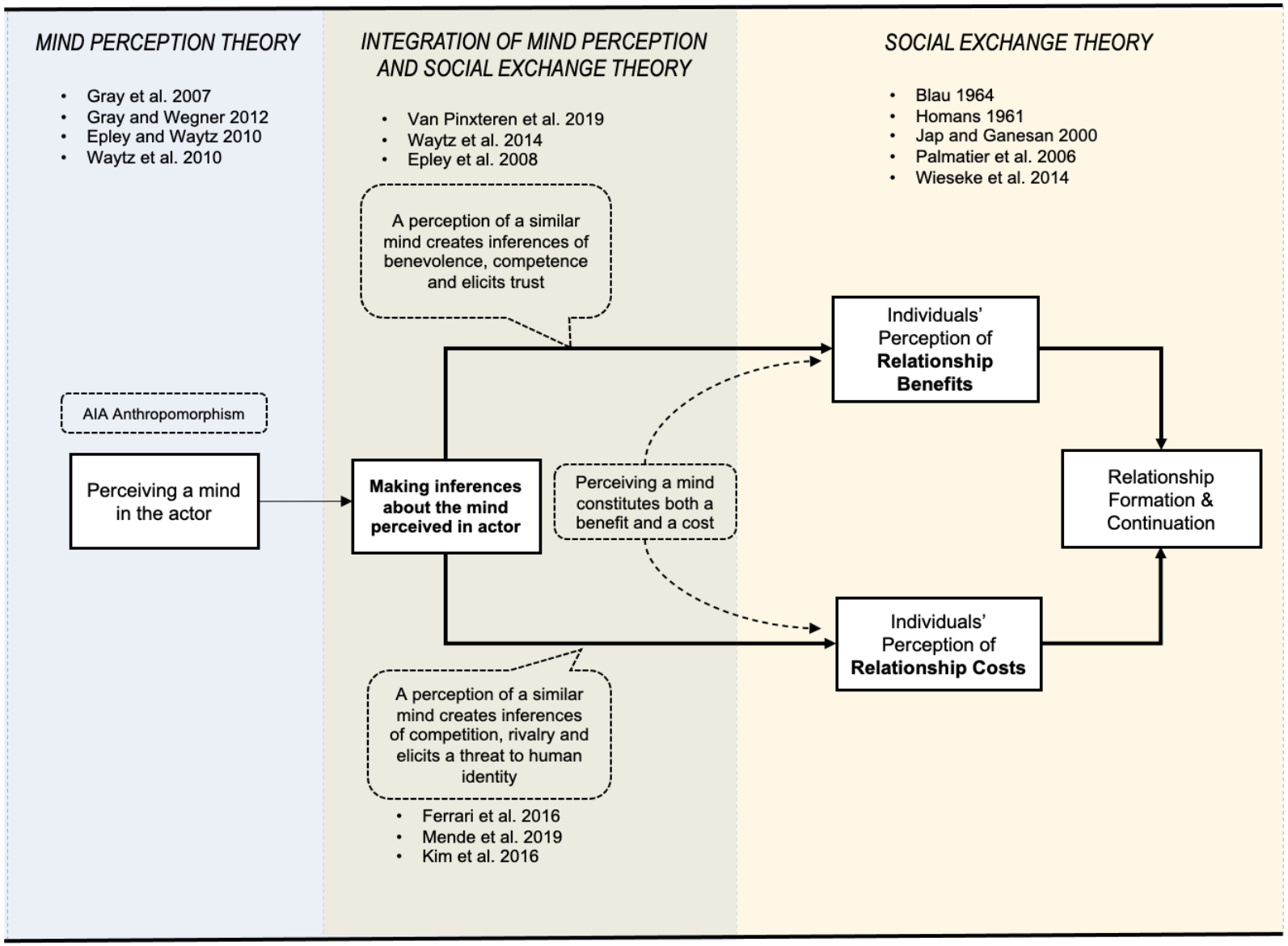


Figure II. Integration of Mind Perception and Social Exchange Theories.



APPENDIX D

Preliminary Consumer Survey

For this preliminary consumer survey, we recruited 300 participants from Prolific without any custom screening except for the current country of residence. After an introduction to the topic and getting consent, we asked the participants whether they use an AIA in their home. Regardless of the answer, we then proceeded to ask all participants about their attitude towards technology in general, their concerns related to their digital personal data, their attitude towards AIAs (specifically, how risky, intrusive and identity-threatening they find the AIAs) in this order. After answering questions about their attitudes, we asked the current AIA users in our participant pool how familiar they were with their privacy settings and how confident they felt protecting the privacy of their data collected by the AIAs. Next, we provided all participants a total of 11 statements related to the practices of AIAs, such as where their data is kept, for how long and for what purposes (e.g. "The provider company (e.g., Amazon, Google) uses my data to analyze my preferences and create individualized offers for me." and "User's voice recordings can be used by the provider company (e.g., Amazon) to improve the Artificial Intelligence Assistant (e.g., Alexa).). We asked the participants whether the provided statement was true or false. The participants had an option to choose that they don't know the answer. The veracity of the statements were corroborated with official websites of AIA provider companies (i.e., Amazon, Google etc.). After this, the participants provided demographic information and were thanked for their contribution.

Preliminary Consumer Interviews

For the preliminary consumer interviews, we recruited 11 current AIA users with a convenience sampling around the institute of one of the authors. In recruiting this pool of participants for interviews, we tried to balance the sample in terms of age, income, family status and time of AIA ownership. The interviews were carried over Zoom with one of the authors

and were recorded. All three of the authors carried out interviews. One of the authors coded and analyzed all the interview data, consulting with other authors should a point of uncertainty arose. A series of questions guided the interviews including the perception of the AIA and how that changed over time, perceived benefits of the AIA and perceptions regarding the use, privacy and knowledge of personal data collected by the AIA. The interviews were semi-structured so the participants were allowed to move to tangents and parallel sub-topics at will. We also asked the participants whether they had any memorable AIA experiences (positive, negative or neutral) and finally asked them about their overall attitude towards technology and artificial intelligence. At the end of the interview, the participants were thanked for their contribution.

Study 1

At the beginning of Study 1, we welcomed the participants with an introduction of the topic of the survey and indicated that we were interested specifically in their use of AIAs at home, in their smart speakers to make sure that any potential AIA use via smartphones outside home should not be reflected in our survey. After this introduction, participants were asked to indicate which AIA they use. After selecting their AIA, the scales for the main independent variables in our study were presented in the order that is provided in Table 3 of the paper. After these measurements, the scales for the control variables were presented. After completing all of the presented scales, the participants also provided demographic information and subsequently were thanked for their contribution.

Approximately 6 months later, the same pool of participants was contacted again. In a similar survey design, after another brief introduction to our topic, the scales for the main dependent variables in our study were presented in the order that is provided in Table 3 of the paper. At the end of the survey, the participants were provided with a comment box to give feedback about the study, if they wished to do so.

CHAPTER 4

ESSAY 3: Social Media Is Shifting The Values In Our Societies: An Increase In Achievement And Conformity

Uysal, Alavi, Bezençon

INTRODUCTION

In the past two decades, social media has emerged as one of the most dominant forces in our lives. From checking notifications on our phones first thing in the morning to scrolling through feeds before going to bed, social media has become an integral part of our daily routine. In 2022, people spent on average 147 minutes on social media per day (Statista 2022). With over 4.59 billion users worldwide in 2022 and growing (Statista 2023), social media occupies a pervasive place in our society. The cultural paradigms can persist for centuries (Abramson and Inglehart 2009; Kalberg 1987), but the rise of social media seems to have caused an unprecedented shift in human society in a matter of two decades. Gaining a comprehensive understanding of the effects of social media on the basic values of individuals is paramount from a research, practice, and societal perspective because values play a crucial role in shaping attitudes, behaviors, and decisions. The paper's core goal is to examine the impact of social media on basic individual values, to better understand how this influential technology is shaping the way we think and act.

While social media has been recognized as a means to expand oneself worldwide and enhance human connection, it has also been linked to mental health issues (Kim and Kim 2017; Østergaard 2017; Valdez et al. 2020). Past research has found associations between higher social media use and lower body satisfaction (Engeln et al. 2020), lower self-esteem (Marino et al. 2018), higher depressive symptomatology (Yoon et al. 2019), higher anxiety (Mackson

et al. 2019) and greater feelings of loneliness and social isolation (Kross et al. 2013; Primack et al. 2017). At the societal level, cross-cultural studies have found that social media usage, including the number of friends, topics discussed, and motivations to use social media differed significantly between cultures (Alhabash et al. 2012; Fong and Burton 2008; Hsu et al. 2015; Kim et al. 2011). However, while people's values and personalities may influence how they use social media (Brännback et al. 2017; Correa et al. 2013; Seidman 2013), to our knowledge, no studies have explored the effect that social media might have had on basic individual values. Previous research has typically viewed values as deeply rooted and stable (Lubinski et al. 1996; Schwartz 2005). However, Calcagni et al. (2019) propose that social media platforms might be new arenas for the co-construction of values in our societies (Calcagni et al. 2019; Gündüz 2017).

To explore the influence of social media on individuals' basic values, we adopt a theoretical framework that explores the interplay between belonging and differentiation motives within the context of social comparison (Brewer 1991; Festinger 1954). We argue that the advent of social media has intensified individuals' motivations for belonging and differentiation. Social media has brought about a significant transformation in the nature of social comparisons, particularly with regards to the intensity and frequency of our exposure to such comparisons. On these platforms, individuals engage in upward comparisons with an idealized version of everyone, often relying on quantifiable metrics such as 'likes' to gauge social approval. Past research indicates that this focus on upward comparisons contributes to a sense of inferiority (Appel et al. 2015; Smith 2000). Coupled with a tendency to self-ruminate, we suggest that this leads to increased anxiety for social media users. With heightened anxiety, individuals seek more approval from their social group to bridge the perceived gap between their own inferiority and the standards set by others. In their quest for approval, individuals aim to differentiate themselves by achieving more, while also conforming to their social group's

norms to maintain and receive social rewards, fulfilling their need for approval through both belonging and differentiation. Specifically, we propose that greater social media exposure will increase achievement and conformity values through heightened anxiety and an increased need for approval.

To examine these propositions, we conducted three studies. In Study 1, we analyzed the longitudinal cross-sectional data from Rounds 7 to 9 of the European Social Survey (ESS) from 15 European nations (N≅80000) (European Social Survey 2016). We supplanted this dataset with country-level social media and control variables. We found that social media exposure fosters achievement and conformity in individuals. In Study 2, we conducted a consumer survey to examine the underlying mechanisms of this effect with a nationally representative sample (N=1000). Study 2 confirmed the finding that greater social media use increased basic individual values achievement and conformity, mediated by increased anxiety and subsequently an increased need for approval. In Study 3, we set up an experimental design where we manipulated participants' social media exposure (N=200) to establish a stronger causal link between social media use and the change in values. We found that the participants who were in the experimental condition with social media exposure had significantly higher scores for achievement and conformity values, compared to the control group which browsed news articles instead of social media. In addition, a longitudinal analysis showed that the experimental groups had their achievement and conformity values increased from the previous measurement, compared to controls.

With our findings, we argue for two main theoretical contributions to the literature on social media and individual values. First, our study contributes to the social media literature (Bayer et al. 2020, Rosenthal-von der Pütten et al. 2019, Yang 2022) by showing that social media has profound effects beyond individual well-being and could shape the individual values of people with extended exposure. Such a fundamental shift in values is likely to impact the

broader cultural landscape. Our results echo the literature on the effects of social media on individuals (e.g., on anxiety) (Dobrean and Pasarelu 2016; Keles et al. 2020; Vannucci et al. 2017) and extend this literature by showing that the effects of social media could go beyond transitory effects and could lead to permanent changes in individuals. Second, even though values are often considered relatively stable (Schwartz 2005; Williams 1967), we propose that social media is at the core of fundamental shifts in many areas of our daily lives, including entertainment, communication, and even our self-concept. By establishing a causal link between social media use and a change in individual values, we show that social media is a paradigm-shifting phenomenon and its effects are even more permeating than previously thought (Akram and Kumar 2017; Amedie 2015; Siddiqui and Singh 2016). We emphasize that individual values are the precursor to all attitudes and behaviors (Ajzen 2012; Hurst et al. 2013; Maio et al. 2006).

Our focus on the benefits of technology often leads us to overlook the potential consequences until they become apparent, and by then, it may be too late to take action (the Collingridge dilemma) (Collingride 1980; Winner 2010). Unlike any other technology before it, social media has become an omnipresent force in the lives of billions of people, shaping our interactions, perceptions, and even our self-worth. Given its pervasive presence, it becomes crucial for society to reflect on our collective responsibility in promoting healthy social media habits and fostering digital well-being. While our findings do not necessarily suggest that social media intensifies inherently negative values, they do underscore the significant impact and shift that a particular digital technology can have on our society. By acknowledging the far-reaching influence of social media and actively contemplating our role in shaping its impact, we can work towards cultivating a healthier relationship with this powerful tool. This involves fostering a sense of self-worth that extends beyond a narrow set of achievements or conforming

to the expectations of others. Through such deliberation and collective efforts, we can strive to harness the potential of social media for positive individual and societal outcomes.

THEORETICAL DEVELOPMENT

To comprehensively explore the influence of social media on individuals' basic values, we adopt a theoretical framework that explores the interplay between belonging motives and differentiation motives within the context of social comparison (Brewer 1991; Festinger 1954). As inherently social beings, humans are driven by two competing motives: the need for belonging to social groups and the desire to differentiate themselves from those groups (Tajfel and Turner 2010). People yearn for a sense of belonging within their social circles, while simultaneously striving to establish their uniqueness. Both belonging and differentiation motives are deeply intertwined with the social environment, as these motivations exist solely in relation to others (Turner et al. 1979).

Humans are innately driven to evaluate themselves by comparing their abilities and attributes with those of their peers (Festinger 1954). Social comparisons serve multiple purposes: individuals engage in social comparisons to assess one's standing and reduce uncertainty about one's own opinions, for self-enhancement, self-improvement, coping strategies, and mood regulation (Wood 1989). The nature of these social comparisons is influenced by individuals' current motivations, leading them to engage in either upward or downward comparisons. For instance, when individuals experience a threat to their self-esteem, they are more likely to engage in downward comparisons to boost their sense of self-worth (Wills 1981). Conversely, upward comparisons can evoke negative emotions (e.g., Tesser et al. 1988), such as anxiety to feel inadequate. The emotional impact of social comparison is determined by both how favorable the comparisons are to oneself and how much attention is focused on oneself rather than others (Rosenthal-von der Pütten et al. 2019). Even more

intriguingly, social comparisons can have significant affective impacts even when they are irrelevant to the outcome being assessed (Dvash et al. 2010).

While social comparisons are not a recent notion, the emergence of social media platforms has introduced an unparalleled accessibility to these comparisons, rendering them readily available at our fingertips whenever we choose to browse through them (Verduyn et al. 2017). Moreover, this availability is accompanied by an unprecedented significance in our daily routines, with individuals worldwide spending an average of 147 minutes per day on social media (Dixon 2022). Consequently, the pervasive influence of social media has fundamentally transformed the manner in which individuals partake in social comparisons within their lives.

In addition significantly magnifying the extent and the intensity of social comparisons in our lives, the advent of social media has also introduced a novel mechanism to the dynamics of social comparisons. Past research shows that activations in the brain's reward network are not only triggered by stimuli such as food or sexual images but also by social interactions, such as sharing something with friends, being liked by others, and disclosing personal information to others (Fareri et al. 2012; Izuma et al. 2008; Tamir et al. 2015). Social media platforms closely reflect these mechanisms, as users frequently engage in activities such as browsing other people's photos, sharing their own content, and seeking validation through likes. Positive feedback and social acceptance, as demonstrated by receiving likes on social media, are experienced as social rewards. The unique aspect of social media is the availability of both social comparison information and "flattering interaction information" (Rosenthal-von der Pütten et al. 2019), including the number of friends, comments on posts, and the number of likes received. This way, social acceptance becomes quantifiable and condensed into a single metric. This striking feature to measure social acceptance intensifies the salience of social comparisons on social media. Previously rather qualitative attributes such as beauty, charisma,

popularity, and perceived interest now revolve around a single numerical value: the number of likes, follows, or retweets gained.

People have striven to fulfill both their motivations for belonging and differentiation in offline settings in the past, and now they do this in the new social media ecosystem. In offline environments, individuals had various dimensions of comparison and referents to restore their positive social distinctiveness. For example, if someone felt inferior in terms of wealth, they could focus on their intellectual prowess as a means of differentiation. However, the dynamics of social media are different. The simplification of social approval into a single metric eliminates the possibility of such multidimensional comparisons. There is one dominance hierarchy that is determined by engagement metrics like the number of likes, comments, and retweets. Therefore, the desire for differentiation becomes more challenging to satisfy because social media platforms primarily showcase individuals' best selves (Hollenbaugh 2021). Downward comparisons, which once provided an avenue for boosting self-esteem, are scarce since everyone's online persona appears flawless (Kross et al. 2013). Everyone engages in upward comparisons with other users' content to seek social approval. Consequently, social comparisons on social media predominantly engender feelings of inadequacy and inferiority (Steers et al. 2014; Warrender and Milne 2020). Thus, people find themselves navigating a new landscape of self-presentation and social validation. The pursuit of positive social distinctiveness becomes a complex endeavor within the online realm, where individuals strive to differentiate themselves while also seeking recognition from their social groups without which the distinctiveness cannot be achieved. In a way, the desire to achieve more to stand out is intertwined with a certain level of conformity to the norms of one’s social group (Schwartz et al. 2012). Consequently, people find themselves in a paradoxical situation.

We argue that social comparison on social media increases peoples’ anxiety, and they yearn for social approval to alleviate it. Ironically, they seek solace in the very platform that

intensifies their anxiety, relying on the social rewards it offers. This heightened anxiety further propels them to seek more approval from their social group, attempting to bridge the perceived gap between their own perceived inferiority and the perceived social standards on social media. Individuals who experience a need for approval are driven to fulfill this need by engaging in specific behaviors. Consequently, displaying personal achievements may become increasingly important to them. This is because gaining approval from others often stems from showcasing accomplishments. However, approval can also be attained through conforming to the values and norms upheld by one's social group. In fact, on social media, the key to gaining social rewards easily is to follow the trends (e.g., TikTok dance trends is a prime example of this). Therefore, we expect that the need for approval induced by social media would lead to an increase in both the pursuit of personal achievements and conformity to group values. We propose two overarching hypotheses:

H1: Greater social media use will lead to an increase in basic individual value achievement.

H2: Greater social media use will lead to an increase in basic individual value conformity.

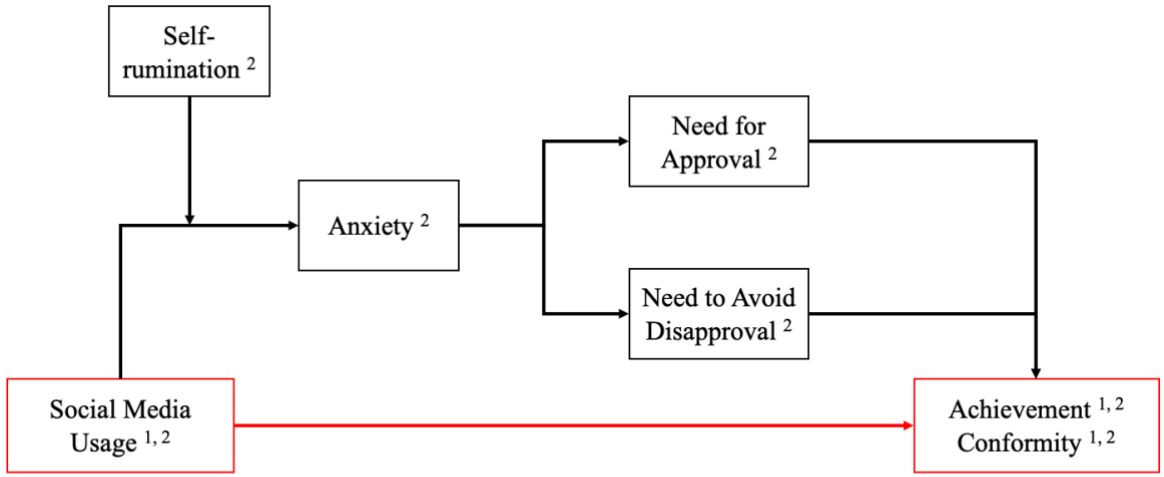
In summary, our theoretical framework highlights the intricate interplay between belonging and differentiation motives within the context of social comparison on social media. Next, we argue for the mechanisms behind these hypotheses.

Social Media, Anxiety, and the Need for Approval

The emphasis on social comparison and the quantifiable metrics of social acceptance on these platforms put pressure on individuals. As they engage in upward comparisons driven by the desire for social approval measured through metrics such as likes, they become more aware of the gap between their perceived inferiority and the perceived standard on social media. This awareness magnifies the feelings of inferiority and self-doubt, fueling anxiety in the social

media user (Jiang and Ngien 2020). This anxiety is characterized by feelings of distress or worry that arise due to

Figure 1. Overview of the conceptual model.



[1] Included in Study 1 (N=79058) *Study 1 included only the main effect.*
[2] Included in Study 2 (N=1000) *Study 2 included the full conceptual model.*
Study 3 includes the experimental manipulation of social media use (N=212).

constant exposure to idealized representations of others' lives, fear of missing out, and the pressure to maintain an online persona. The perpetual accessibility of social media, available at any time and any place, means that individuals are continually exposed to triggers for social comparison (Bayer et al. 2020). This constant exposure to idealized versions of others' lives further exacerbates these feelings, creating a cycle of comparison and anxiety that can be difficult to break free from (Alfasi 2019; Butzer and Kuiper 2006). This hypothesis is in line with previous work that has shown similar effects of social media use (Bonnette et al. 2019, Jiang and Ngien 2020; Zheng et al. 2020). We propose that individuals who are prone to self-rumination, characterized by repetitive and negative self-focused thoughts, may be particularly vulnerable to this heightened anxiety (Lannin et al. 2021). Therefore, we hypothesize:

H3: Greater social media use will lead to an increase in anxiety.

H4: Self-rumination moderates the relationship between social media use and anxiety, such that the positive effect of social media use on users' anxiety is more pronounced for higher self-rumination.

The experience of heightened anxiety among social media users profoundly influences their pursuit of approval from their social group. The desire for social approval acts as a coping mechanism to alleviate their anxiety (Karasar and Baytemir 2018; Lobel et al. 1987). As they further engage in social comparisons and perceive a significant disparity between their perceived inferiority and the seemingly perfect social standards presented online, their anxiety deepens. This heightened anxiety becomes a driving force that propels them to actively seek more approval from their social circle. By getting habituated to this ecosystem, that is, by extensive and repeated social media use, the effects of anxiety and need for approval grows stronger and more pronounced.

When people are anxious about their perceived inferiority, they engage in two distinct strategies (Berger et al. 1977). First, they seek approval, aiming to gain positive evaluations from others as a means of bridging the gap between their perceived inferior self and the ideal self. Second, they strive to avoid disapproval, a defensive strategy, aiming to prevent negative assessments or criticisms from others in order to protect themselves (Berger et al. 1977). These coping strategies are rooted in the heightened anxiety experienced within the social media context. We argue that when individuals experience heightened anxiety, their craving for reassurance intensifies, leading to an increased need for approval (Rector et al. 2011). In the midst of anxiety, individuals are more susceptible to seeking positive feedback, recognition, and appreciation from others (Lobel et al. 1987; Steers et al. 2016). Therefore, we hypothesize:

H5: Heightened anxiety in individuals will lead to a greater need for approval.

In addition to seeking positive feedback, individuals grappling with heightened anxiety also exhibit an increased need to avoid disapproval (Berger et al. 1977). Anxiety can trigger self-

doubt, self-criticism, and a heightened fear of judgment from others (Braslow et al. 2012; Iancu et al. 2015). Consequently, individuals become hyper-aware of potential criticisms, failures, or perceived shortcomings. To mitigate negative evaluations, they engage in behaviors aimed at avoiding disapproval and criticism (Berger et al. 1977). This may involve conforming to social norms, suppressing dissenting opinions, or employing various self-presentation strategies to maintain a favorable image (Bergquist and Nilsson 2019). Seeking to avoid disapproval becomes a defensive mechanism rooted in the desire to protect oneself from the potential threats associated with heightened anxiety. It serves as a means to secure acceptance, ward off rejection, and maintain a sense of belonging within their social circles. Therefore, we hypothesize:

H6: Heightened anxiety in individuals will lead to a greater need to avoid disapproval.

A Shift in Values

Next, we argue that the need for approval plays a significant role in shaping individuals' values within the social media landscape. Through the approval they seek, individuals aim to cultivate a positive social image and enhance their perceived worth within the social media ecosystem. We propose that people do this by aligning their behaviors, self-presentation, and content creation with the ideals that are highly regarded by their peers, that is, pursuing a sense of belonging by conforming to the norms of their social group. In addition to a sense of belonging, people are also motivated to sufficiently differentiate themselves from their group (Brewer 1991). In our investigation, we focus on two basic individual values emerging from these two motives, achievement and conformity (Schwartz 1992). We follow the definitions provided by Schwartz, and define achievement value as success according to social standards. We define conformity as compliance with social norms and avoiding upsetting other people (Schwartz et al. 2012).

Broadly, we argue that the pursuit of approval propels individuals also towards the attainment of achievements to reach the norms communicated by social media. However, we further argue that the need for approval not only influences individuals' subsequent behaviors, perhaps in a transient manner, but also shapes their value orientation, leading to a lasting change in individual values. People use social media constantly, so values can change permanently. Past literature shows that environmental cues can activate different values in people and prime certain behaviors (Bardi et al. 2009). A single event might cause a change in values, but if people are exposed to the event just once, the changes are usually temporary. However, research suggests that longer term changes in values do still occur, particularly through primes that are leading to the activation of the same values repeatedly. This gradually strengthens the activated value until it becomes a central and dominant orientation for the individual, affecting perception and behavior (Bardi and Goodwin 2011). This idea perfectly mirrors the dynamics observed on social media platforms, where the behaviors are repeated over and over again.

The need for approval becomes a driving force for individuals to focus on achievement as a means of standing out from others. Individuals with a strong need for approval are more likely to invest greater efforts and resources into attaining accomplishments that garner recognition and validation from their social environment. This pursuit of achievement serves as a strategic pathway for individuals to differentiate themselves and stand out from their peers, thereby increasing their perceived worth within their social context (Sanchez and Crocker 2005; Sargent et al. 2006). Therefore, we hypothesize:

H7: A greater need for approval will increase the individual's achievement value.

The motivation to avoid disapproval stems from individuals' fear of rejection and social exclusion, yet it can serve as a powerful motivator. The fear of negative evaluation prompts individuals to strive for achievement and to prove their worth (Berger et al. 1977). This fear

can also fuels motivation and competitiveness, pushing individuals to work harder and set ambitious goals. Furthermore, negative evaluations foster self-reflection, helping individuals identify areas for improvement and develop strategies for achievement. Overall, we argue that individuals with a strong need to avoid disapproval channel their efforts into achievement, to overcome perceived deficiencies and maintain their positive standing in their social environment.

H8: A greater need to avoid disapproval will increase the individual's achievement value.

We argue that a heightened need for approval will lead to an increased inclination towards conformity, whereby individuals conform to social norms, expectations, and group behavior in order to maintain their positive social standing and continue receiving approval. This proposition aligns with past research that has shown that on social media "people like what other people like." (Rosenthal-von der Pütten et al. 2019). In the pursuit of success on social media, which entails collecting social rewards such as likes, shares, and followers, individuals are compelled to adhere to the established rules and norms of the platform rather than deviating from them. This behavior stems from the understanding that aligning with popular trends, conforming to popular opinions, and adhering to the expectations of the online community enhance the likelihood of receiving positive feedback and approval. Consequently, individuals with a greater need for approval are expected to exhibit a higher degree of conformity as they strategically conform to the rules and dynamics of social media in order to maintain their desired social status and attain continued approval from their social group. Therefore, we hypothesize:

H9: A greater need for approval will increase the individual's conformity value.

We argue that an increased need to avoid disapproval will intensify individuals' motivation to conform to the attitudes, expectations, and norms of their social group. This proposition stems

from the recognition that people possess an inherent desire to evade the negative social consequences (e.g., rejection or social exclusion) (Davis 1997; Leary et al. 1995). By aligning themselves with the norms and expectations of their groups, individuals strategically aim to avoid such adverse social outcomes. This inclination towards conformity is deeply rooted in the lessons individuals learn from both social media and everyday life, where conforming to social norms and group expectations is often rewarded with positive outcomes (Bearden and Rose 1990; Ridgeway 1978). Conversely, deviating from these norms and expectations may elicit negative evaluations. Consequently, individuals with a high need to avoid disapproval may find themselves motivated to conform to the standards set by their social group as a means of evading social sanctions and safeguarding their social standing. Therefore, we hypothesize:

H10: A greater need to avoid disapproval will increase the individual's conformity value.

STUDY 1: EXPLORING THE ESS DATASET

Procedure

Study 1 aims to test H1 and H2 to investigate the effect of social media exposure on achievement and conformity. To this end, we analyzed data from the European Social Survey (ESS) Rounds 7 to 9 (2014-2018) from 15 European nations. Due to the limited availability of consistent social media data to match with ESS data, rounds prior to 2014 were not included. A total of 81023 participants were initially included in the analysis (51.85% female, M_{age}= 49.8). 39275 participants were included in the final analysis. The reason for such a large exclusion was missing data issues, both random and systematic. Some of our key variables were not measured across ESS rounds, which forced us to keep only the participants with complete data points.

Measurements

The ESS dataset provided us with measurements of achievement and conformity values (Schwartz 1992), as well as several relevant control variables such as age, gender, income, household size, and internet use (European Social Survey 2016). As ESS does not contain any social media-related measurements, we created a proxy for social media exposure by creating a country-level variable, social media penetration, which indicates the percentage of daily active social media users as a fraction of the whole population, in a given country, in a given year. This data was extracted from DataReportal (DataReportal 2018). To account for the fact that social media is heavily used by younger people (Anderson and Jiang 2018; Auxier and Anderson 2021; Correa et al. 2010), we used the interaction term of social media penetration and age as the proxy for each individual's social media exposure.

Control variables

We included a broad set of theoretically grounded control variables in the model estimation to reduce the likelihood of endogeneity issues due to omitted variable bias (Sande & Ghosh, 2018) and to assess the stability of the hypothesized effects. We added country-level economic indexes as control variables that have been related to changes in individual values (Inglehart and Abramson 1994; Inglehart and Flanagan 1987), such as GDP, Gini index, and inflation. In addition, we added the population of the country as a control as it has been linked to values and income equality (Inglehart and Abramson 2009; Kondo et al. 2012). Finally, as a conceptually relevant control, we added the level of internet infrastructure in the country, measured as the percent of households in a country with broadband internet access (OECD 2023). These variables were obtained from The Organization for Economic Co-operation and Development (OECD) database (OECD 2023). A table of correlations between all variables is provided in Table 1.

Model specification and results

To test whether social media exposure increases the basic individual values of achievement

Table 1. Correlations table, all studies.

Study 1 Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**
(1) Conformity	1.000												
(2) Achievement	0.158	1.000											
(3) SM Penetration	-0.038	-0.067	1.000										
(4) Age	0.183	-0.261	0.034	1.000									
(5) Internet Use	-0.142	0.089	0.107	-0.384	1.000								
(6) GDP (log)	-0.075	-0.099	0.397	0.038	0.258	1.000							
(7) Gini Index	-0.044	-0.015	0.099	0.038	-0.086	-0.149	1.000						
(8) Population	-0.053	-0.062	-0.338	0.015	0.025	-0.071	0.432	1.000					
(9) Inflation	0.049	0.067	0.572	-0.032	-0.111	-0.422	-0.028	-0.069	1.000				
(10) Income	-0.076	0.062	*-0.001*	-0.177	0.293	0.037	-0.072	-0.018	0.039	1.000			
(11) Internet Access	-0.051	-0.081	0.387	0.030	0.217	0.737	-0.229	0.052	-0.441	0.070	1.000		
(12) Household Size	-0.017	0.126	-0.076	-0.417	0.080	-0.117	-0.048	-0.041	0.074	0.337	-0.091	1.000	
(13) Education Level	-0.112	0.071	0.040	-0.178	0.361	0.176	-0.177	0.023	-0.063	0.391	0.189	0.037	1.000
(14) Gender	-0.010	-0.093	*0.007*	0.032	-0.077	-0.027	0.031	-0.007	0.012	-0.093	-0.030	-0.019	-0.030

Study 2 Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	
(1) Conformity	1.000											
(2) Achievement	*0.055*	1.000										
(3) SM Use	*0.013*	0.247	1.000									
(4) Need for Approval	0.350	0.206	0.160	1.000								
(5) Need to Avoid Disapproval	0.236	0.101	0.171	0.506	1.000							
(6) Anxiety	*0.024*	0.080	0.250	0.176	0.404	1.000						
(7) Age	*0.070*	-0.386	-0.369	-0.183	-0.273	-0.335	1.000					
(8) Internet Use	*-0.041*	0.089	0.189	*-0.001*	*0.012*	0.107	-0.150	1.000				
(9) Income	*-0.035*	0.165	-0.105	*0.013*	*-0.040*	-0.116	*-0.045*	*-0.012*	1.000			
(10) Household Size	*-0.002*	0.129	0.105	*0.033*	*0.052*	*0.052*	-0.287	*-0.025*	0.132	1.000		
(11) Education Level	*-0.033*	0.146	*-0.019*	*0.044*	*0.069*	*0.015*	-0.101	0.083	0.269	*-0.023*	1.000	
(12) Gender	-0.140	*0.024*	*-0.077*	-0.098	-0.174	-0.148	*-0.020*	0.139	0.085	*0.011*	*0.012*	

Study 3 Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
(1) Difference in Conformity	1.000					
(2) Difference in Achievement	0.208	1.000				
(3) Conformity	0.363	0.210	1.000			
(4) Achievement	*-0.087*	0.341	*0.136*	1.000		
(5) Age	*0.072*	*-0.025*	*0.027*	-0.342	1.000	
(6) Income	*0.037*	*-0.033*	*-0.068*	*0.049*	*-0.071*	1.000
(7) Gender	*0.036*	*-0.025*	-0.229	*-0.114*	*0.078*	*0.083*

SM=Social Media, GDP=Gross Domestic Product. Gender is coded as 1=Female, 2=Male. All correlations are significant at 1% significance level, except for those marked in *italic*.

and conformity, we ran multilevel mixed-effects linear regression models. We linked the social media proxy variable as the key independent variable to values achievement and conformity as dependent variables. We ran two separate regression analyses, one with each dependent variable. First, we ran the models without controls (Model 1), then only with individual-level controls (Model 2), and finally with both individual and country-level controls (Model 3). The models with the full list of control variables showed the best fit out of the three. We report the results for all three models in Table 2. We estimated all models using Stata 16 (StataCorp, 2019).

Results

The results showed a significant effect of the independent variable, social media exposure, on both basic individual values achievement (b = -.001, $p < .05$) and conformity (b = -.001, $p < .001$). Since our independent variable is an interaction of social media penetration in a country and the age of the individual, we observe negative coefficients indicating that the effects

emerge in young people, but less so in old people who might be less exposed to social media. These results support H1 and H2 and remained stable under the robustness checks.

As expected, the country's inflation and internet infrastructure as well as individuals' income, education level, and gender all were significant predictors of both achievement and conformity values.

Robustness Checks

To account for potential endogeneity in our model estimation, we conducted a copula-based approach and then the instrumental variable method to address potential endogeneity issues. (Bowden and Turkington 1990; Park and Gupta 2012). Our results remained stable under both robustness checks. We report detailed results in Table I in the Appendix.

STUDY 2: HOW SOCIAL MEDIA IMPACTS ACHIEVEMENT AND CONFORMITY

Procedure

In Study 2, we aimed to investigate the underlying mechanisms of the results we found in Study 1 and tested eight hypotheses, H3 to H10. Specifically, we wanted to explore how social media use impacts individual values. For this purpose, we conducted an online consumer survey. We used a nationally representative sample of 1000 participants based on age, gender, and ethnicity. All of the participants were residents of the United Kingdom that were recruited through Prolific (M_{age}= 44.98, 51% female). 50 participants were excluded from the analysis due to missing demographic data provided by Prolific, and the final sample included 950 participants.

Measurements

Main variables

First, our key independent variable of social media use comprises the total time per day that a user spends on social media. We asked the participants which of the social media platforms they use, among the following: Facebook, Instagram, Twitter, Snapchat, TikTok, and LinkedIn.

We measured daily social media use separately for each social media platform using sliders, reported in hours and minutes. The sum of all social media use reported in six variables constitutes our independent variable of social media use. We measured anxiety (Pilkonis et al. 2011), need for approval and avoidance of disapproval (used as one combined scale in the cited study) (Rudolph et al. 2005), achievement and conformity (Schwartz et al. 2012), and self-rumination (Trapnell and Campbell 1999) with items from established scales adapted to our context.

Control variables

We included the level of education, income, age, and gender of the participants since all of these variables have been shown to impact basic individual values (Bakan 1966; Gërxhani and van de Werfhorst 2013; Inglehart 2020; Ready et al. 2002). We also included ethnicity and country of origin as control variables to account for cross-cultural differences that have been demonstrated in past research (Inglehart 2004). Finally, we also included overall internet use as a control to distinguish social media use from other internet-related activities. All scales conform to the prescribed values for the item reliabilities, composite reliability (CR) and average variance extracted (AVE). The complete list of measurement items including control variables, scale reliabilities, and the order of presentation can be found in Table II in the Appendix.

Model specification and results

To test whether social media use increases the basic individual values of achievement and conformity through elevated anxiety and subsequently an elevated need for approval, we specified a structural equation model as follows: we linked social media use to anxiety (H3), then anxiety to need for approval (H5) and to need to avoid disapproval (H6), then both approval variables to achievement and conformity (H7-H10). In addition, we added self-rumination as a moderator for the link between social media use and anxiety (see Figure 1 for

Table 2. Results of Study 1.

	Model 1		Model 2		Model 3	
	Achievement	Conformity	Achievement	Conformity	Achievement	Conformity
Predictors						
Social Media Penetration	-.005 (.001)***	-.009 (.002)***	.012 (.005)*	.010 (.005)	.012 (.015)	.030 (.012)*
Age	-.015 (.001)***	.010 (.001)***	-.015 (.001)***	.008 (.001)***	-.015 (.001)***	.009 (.001)***
SM Penetration X Age (IV)	-.001 (.001)*	.001 (.001)***	-.001 (.001)**	-.001 (.001)***	-.001 (.001)*	-.001 (.001)***
Controlling for individual characteristics[1]	No	No	Yes	Yes	Yes	Yes
Controlling for country characteristics[2]	No	No	No	No	Yes	Yes
Observations	79058	78769	43486	43323	39420	39275
AIC	242408.401	233861.052	132711.4	128208.7	120491.758	116372.986

*** p<.001; ** p<.01; * p<.05. SM= Social Media. AIC= Akaike Information Criterion. IV= Independent variable used in Study 1. [1] Internet use, Income, Household size, Education Level, Gender, Country of participant, Year survey taken. [2] Log(GDP), Gini index, Population, Inflation, Internet infrastructure.

an overview of the conceptual model). As controls, we included social media use for all paths to analyze and control for the direct links between social media use and the mediators. In addition, we analyzed the indirect and total effects of social media use on achievement and conformity. We estimated this model using Stata 16 (StataCorp, 2019) including 950 observations. The results of this study are presented in Table 3.

Direct effects

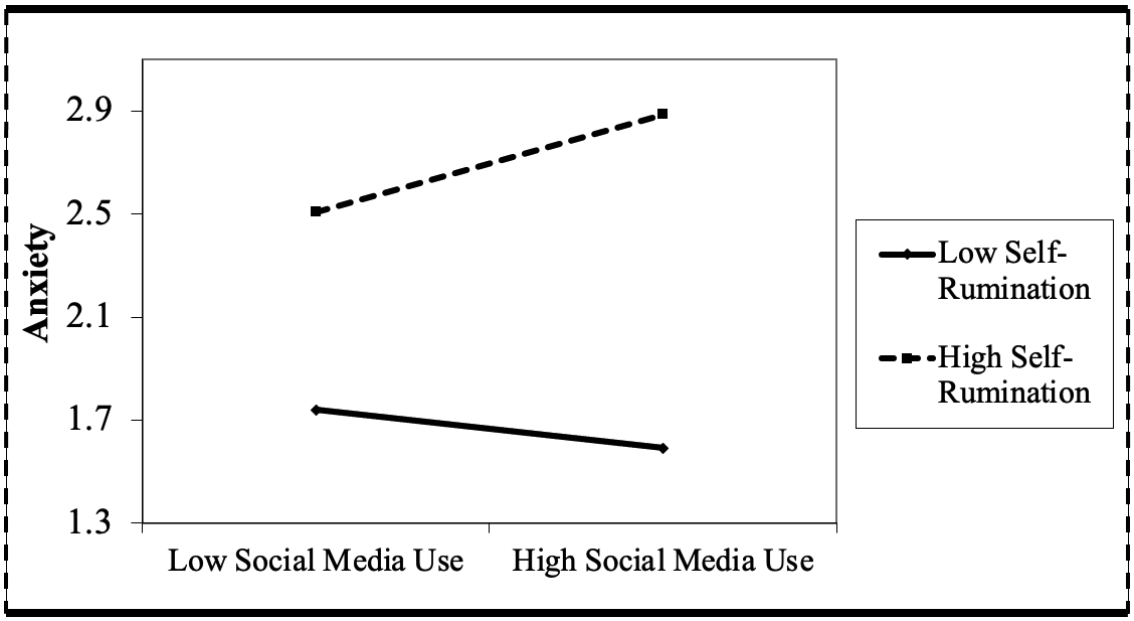
For testing the formal hypotheses, we relied on the fully specified model including the full set of control variables. We analyzed the direct links between social media use and three mediators as well as the dependent variables. The results showed that greater social media use did not have a significant direct effect on the anxiety of the user (b = .001, p = .06). H3, which hypothesized a direct effect of social media use on anxiety was hence rejected. However, greater anxiety significantly increased both the need for approval (b = .094, p < .01), and the need to avoid disapproval (b = .396, p < .001). These results provide support for H5 and H6. Subsequently, a greater need for approval increased both achievement (b = .267, p < .001) and conformity (b = .396, p < .001) whereas the need to avoid disapproval had a positive significant effect only on conformity (b = .095, p < .01) but not achievement (b = -.058, p = .11). Our findings supported H7, H8 and H10, while H9 was rejected. Social media use did not have a significant direct effect on need for approval, achievement, or conformity, indicating a fully mediated effect.

Interaction effects

All variables used in the interaction terms were mean-centered. We found that the interaction of self-rumination and social media exposure had a significant effect on anxiety (b = .001, p < .001). Those who self-ruminate were more susceptible to experience anxiety as a result of social media use (Figure 2). This result supports H4 and provides insight into the role of self-rumination in social media use fostering anxiety in individuals. On the other hand, individuals

who engage less in self-rumination may be less likely to internalize social media comparisons and are therefore exhibit less social media-induced anxiety.

Figure 2. *Study 2:* Interactive effect of social media use and self-rumination on anxiety.



Indirect effects

The analysis of the indirect effects showed that greater social media use significantly increased both values achievement and conformity. Specifically, greater social media use significantly increased achievement, an effect serially mediated by anxiety and a need for approval (b = .001, $p < .05$), but not through anxiety and a need to avoid disapproval (b = -.001, $p = .14$). Greater social media had a significant indirect effect on conformity, serially mediated by both anxiety and a need for approval (b = .001, $p < .05$), and by anxiety and a need to avoid disapproval (b = .001, $p < .05$). This result demonstrates a fully mediated effects of social media use on achievement and conformity, as well as elucidating the mechanism through which this effect occurs. The significant indirect effects lend support to H1 and H2. There was also a direct effect of social media on achievement (b = .001, $p < .001$) but not on conformity (b = -.001, $p = .26$). However, the significant direct effect of social media on achievement was not stable under robustness checks.

Controls

In line with past literature, we also report the notable significant effects of the control variables. Age and income had significant negative effects on anxiety, such that being younger and having less income predicted more anxiety (Age: b = -.014, p <.001; Income: b = -.107, p < .01). Overall, gender had a significant effect on anxiety, such that being a female predicted higher anxiety than being a male (b = -.160, p < .01). In addition, age was a significant predictor of the need for approval (b = -.007, p < .001) and the need to avoid disapproval (b = -.015, p < .001), such that being younger predicted a greater need for both. Age was also a significant predictor of both values achievement (b = .010, p < .001) and conformity (b = -.007, p < .001), such that being younger people predicted higher scores of achievement but lower scores of conformity. There was a significant effect of gender only on conformity (b = -.189, p < .01), such that being female predicted higher scores in conformity. All significant effects of controls were in line with our expectations, based on past literature (Al-Qaisy 2011; Chauhan et al. 2020; Rudolph et al. 2005; Schwartz et al. 2012; Stankovska et al. 2016).

Robustness checks

The results remained stable after conducting a copula-based approach and then the instrumental variable method to address potential endogeneity issues. (Bowden and Turkington 1990; Park and Gupta 2012). Detailed results are presented in Table III and Table IV in the Appendix.

STUDY 3: THE IMPACT OF SOCIAL MEDIA EXPOSURE ON ACTIVATING VALUES

Procedure

In Study 3, we aimed to demonstrate the causal effect of social media use on activating individual values with an experimental setup. For this purpose, we conducted an online experiment. In this experiment, we intended to examine the immediate effect of social media use on subsequent individual value measurements. The study comprises three experimental conditions: two conditions with social media use and a control condition without social media

Table 3. Results of Study 2.

Path		Full Model	[95% CIs]	
Main links		*Coef. (SE)*		
Social Media Use [H3]	**→ Anxiety**	.001 (.001)	-.000	.001
Anxiety [H5]	**→ Need for Approval**	.094 (.030)**	.035	.153
Anxiety [H6]	**→ Need to Avoid Disapproval**	.396 (.039)***	.320	.471
Need for Approval [H7]	**→ Achievement**	.267 (.051)***	.166	.366
Need for Approval [H9]	**→ Conformity**	.386 (.045)***	.298	.474
Need to Avoid Disapproval [H8]	**→ Achievement**	-.058 (.037)	-.130	.013
Need to Avoid Disapproval [H10]	**→ Conformity**	.095 (.032)**	.032	.157
Interaction effect & Main effects of the moderator				
SM Use X Self-Rumination [H4]	**→ Anxiety**	.001 (.001)***	.000	.001
Self-Rumination	→ Anxiety	.517 (.028)***	.463	.572
Control paths				
Social Media Use	→ Achievement	.001 (.000)***	.000	.002
Social Media Use	→ Conformity	-.000 (.000)	-.001	.000
Social Media Use	→ Need for Approval	.001 (.000)***	.000	.001
Social Media Use	→ Need to Avoid Disapproval	.001 (.001)	-.000	.001

*p < .05, **p < .01, ***p < .001; standardized coefficients, SE=Standard Error. Hypothesized parts are written in **bold**.
In the model estimation, the following control variables were included: Age, Gender, Country of origin, Ethnicity, Household size, Income level, Education level, Internet use.

use. To allow for both between and within-subjects analyses, we invited back the participants from Study 2, six months later. This way we had the measures of individual values before the treatment in this experimental study (measurements from Study 2). We invited all the participants from the Study 2 cohort, with the only pre-condition of being a Facebook and LinkedIn user. 212 participants completed the experiment. All of the participants were residents of the United Kingdom that were recruited through Prolific initially for Study 2 (M_{age}= 42.70, 44% female). At the beginning of the experiment, the participants were randomly assigned to one of the three conditions. In the first condition, the participants were asked to log in to their LinkedIn account and browse their LinkedIn feed for five minutes. They were provided a link to reach their LinkedIn feed, and they could not proceed with the experiment before the five minutes were elapsed. In the second condition, the participants were asked to browse their Facebook feeds instead. The third condition was the control condition where the participants were redirected to the BBC website to browse highlights of news articles instead

of browsing social media. The BBC presents short highlights of news articles with a photo and a brief description on its main page, and these highlights are similar to social media posts. After this treatment, they completed the rest of the survey and were thanked for their contribution.

Measurements

We measured achievement, conformity, anxiety, need for approval, need to avoid disapproval, self-rumination, and social media use with the same items used in Study 2. At the end of the survey, we also measured internet use, age, gender, household size, income and education level as control variables, using the same measurements scales in Study 2. All scales conform to the prescribed values for the item reliabilities, composite reliability (CR) and average variance extracted (AVE). The list of all measurement items, scale reliabilities and the order of presentation is provided in Table II in the Appendix.

Results

Attention and Manipulation Checks

In order to ensure the efficacy of the experimental manipulations and maintain a high level of survey-taker engagement, a series of measures were implemented. Two attention checks were incorporated, requiring participants to select predetermined responses to specific questions. Both the first wave (Study 2 cohort) and the second wave (Study 3 cohort) underwent two attention checks during each respective study. In total, each participant had to answer all four attention checks correctly to be included in the final analysis.

Right after the manipulation, we asked the participants in all conditions to compose a concise summary consisting of a single sentence for three social media posts or highlights of news articles they had browsed. Participants who failed all attention checks (N=1) or neglected to provide these brief summaries for the three encountered posts/articles (N=1) were excluded from the analysis. The final sample included 210 participants.

Change in values

As the dependent variable, first, we used the difference in the measurements of values achievement and conformity between the first and the second wave (t_2-t_1). We call these variables *difference in achievement* and *difference in conformity*. Between these measurements which were 6 months apart, for people in the control condition, we would expect no change in the values. In the two experimental conditions where the participants were exposed to social media, we expect an increase in the achievement and conformity values, compared to the first wave. In the second analysis, we used achievement and conformity values (as measured in Study 3) as dependent variables to analyze the differences between the three experimental groups. For this analysis, according to our hypotheses, we would expect to have higher overall achievement and conformity scores in the two experimental groups that were exposed to social media, compared to the control group. If social media use can in fact activate achievement and conformity values, we should observe this difference between groups.

The results of a one-way analysis of variance (ANOVA) revealed a significant effect of the experimental condition on the difference in achievement ($F(2, 208) = 4.36$, $p = .01$) and a marginally significant effect on the difference in conformity ($F(2, 208) = 2.64$, $p = .07$). These results support H1 and H2, indicating that social media use increases achievement and conformity values. Contrast analysis revealed that the two groups that were exposed to social media jointly had a higher increase in achievement value compared to the control group ($F(2, 200) = 4.36$, $p = .01$). Two experimental groups each separately significantly differed from the control group as well, with the Facebook group ($F(1, 200) = 7.99$, $p = .005$) showing a stronger effect than the LinkedIn group ($F(1, 200) = 4.67$, $p = .03$). However, the same contrasts were not found to be significant for conformity.

In addition to the within-subjects approach in the first analysis, we also analyzed the achievement and value measurements across three experimental groups. The results of a contrast analysis showed that both Facebook and LinkedIn treatment groups had marginally

higher overall achievement scores compared to the control (Facebook: $F(1, 195) = 2.70$, $p = .10$; LinkedIn: $F(1, 195) = 3.05$, $p = .08$). However, the contrast analysis did not reveal any differences between the two treatment groups and the control group for conformity.

These findings show a clear pattern for achievement, but not for conformity despite a trend towards the hypothesized direction in the first analysis. In addition, even though the contrasts between Facebook and LinkedIn groups were not significant, in the Facebook group, a stronger effect was observed on achievement. While this is not conclusive in our findings, exposure to different social media platforms could have potentially different effects (e.g., Albahash and Ma 2017; Hildebrand and Schlager 2019).

GENERAL DISCUSSION

Social media platforms allow for constant social comparison of oneself against others, and we show that this leads to feelings of anxiety in social media users. We find that, in order to alleviate these negative emotions, individuals may seek approval from others by conforming to group norms and striving for achievement. On social media, the dynamics of social groups play a crucial role in shaping individuals' social identities (McKenna and Green 2002; Taylor et al. 2022). In addition, social comparisons magnify people’s perceived inadequacies and motivate them to strive for more in order to obtain approval from their peers. As a result, people seek approval and acceptance from others within their social group, leading to conformity with the group's norms and values.

Overall, the findings show that social media use can have a significant impact on individual values achievement and conformity. In Study 1, with an analysis of a longitudinal dataset, we show a general long-term positive effect of social media on achievement and conformity values. As predicted by past literature, important predictors of individual values such as household income, country’s inflation, and overall internet use emerged as strong predictors of values. However, even when controlling for the most important factors, social

media exposure emerged as a significant predictor of an increase in achievement and conformity.

Study 2 focused on the process of this value change and revealed that social media use impacts achievement and conformity values through heightened anxiety and a need for approval. Study 2 provides additional insights into the suggestion that social media use leads to increased anxiety, indicating that individuals who engage in higher levels of self-rumination may be particularly susceptible to social media-induced anxiety. Self-rumination could influence the extent to which individuals internalize social comparisons on social media and the subsequent impact on their anxiety levels. In our findings, self-rumination emerges as a potentially key moderator that may have a significant impact on individual susceptibility to harmful effects of social media. We find that, while heightened anxiety increases the need for both getting approvals and avoiding disapprovals, the effect of the need for approval seems to be stronger on values compared to the need to avoid disapproval. The results do not allow for a conclusive takeaway, but we suggest that this trend is in line with the mechanics of social media where people seek and get approvals, positive evaluations in terms of likes, comments, and engagement. However, in most social media platforms there is no “dislike” button to directly represent a disapproval to be avoided. Therefore, the need for approval could be a stronger mediator for the effects of social media.

Finally, Study 3 employed an experimental design to provide further evidence regarding the causal relationship between the use of social media and its impact on achievement and conformity. Our findings revealed that the groups exposed to social media activate achievement and conformity values to a greater extent than the control group (within-subjects analysis). This effect was marginally significant for conformity. These results provided additional evidence supporting the causal effect of social media on individual values. In our study, we provided the participants with a brief exposure to social media, limited to just five

minutes. However, it is important to acknowledge that in real life, individuals often experience prolonged and frequent exposure to social media over the course of many years. Such extended periods of engagement can lead to repeated activation of personal values, which likely paves the path to permanent value change (Bardi and Goodwin 2011). This finding suggests that exposure to social media can have an immediate impact on individual values, in addition to its long-term effects demonstrated in Study 1. This finding aligns with past literature on value priming and activation (Bardi and Goodwin 2011; Maio et al. 2019), further advancing our understanding of the influence of social media on individual values.

In three studies, we show that social media can be an important catalyst for a shift in individual values.

Theoretical contributions

With our findings, we argue for three theoretical contributions to the literature on social media and individual values. First, we demonstrate that social media has far-reaching effects that extend beyond individual well-being, shaping the fundamental values of individuals who are extensively exposed to it. This finding represents a shift in our understanding of social media's influence (Akram and Kumar 2017; Amedie 2015), suggesting that it has the potential to reshape broader cultural landscapes. Our results align with prior research on the effects of social media on individual outcomes, such as anxiety (Dobrean and Pasarelu 2016; Keles et al. 2020; Vannucci et al. 2017) which we replicate, but also extend this literature by illuminating the enduring impact of social media, capable of inducing permanent changes in individuals' values.

Second, we introduce self-rumination as an important moderator of social media's negative implications for mental health. Our findings reveal that anxiety arises predominantly in individuals with a high propensity for self-rumination when engaging with social media (see Lannin et al. 2021 for a different perspective on the role of self-rumination). This finding could

potentially reconcile the conflicting effects of social media reported in previous studies, such as social connectedness and depression (Allen et al. 2014; Ryan et al. 2017). By identifying self-rumination as a key factor, we shed light on the underlying mechanisms that shape the impact of social media on mental well-being.

Third, our work underscores the pivotal role of social media in instigating fundamental shifts across various facets of our daily lives, encompassing entertainment, communication, and even our self-concept. By establishing a causal link between social media usage and changes in individual values, we highlight the pervasive influence of this phenomenon. Previous literature on value change presents contrasting findings. While some studies have reported only minimal shifts in values (Lubinski et al. 1996; Schwartz, 2005), others have presented evidence of more substantial transformations (Rokeach, 1973; Sheldon, 2005). Our findings add valuable insights to this discourse on value change by acknowledging social media as a transformative force in society within a relatively short timeframe of fewer than two decades (Bardi and Goodwin 2011; Maio et al. 2019). Furthermore, our study extends this literature by highlighting the influential role of external factors (e.g., new, disruptive technologies) in shaping our values. It would be beneficial for future research to explore the potential impact of other paradigm-shifting new technologies, such as advanced artificial intelligence, on individual values. For instance, the emergence of chatGPT might potentially induce a shift towards conservation values (e.g., security) rather than openness values (e.g., stimulation) among individuals due to an increase in the perceived threat to human identity.

Implications

Our findings have important implications for various stakeholders, including practitioners, policymakers, educators, and society as a whole. First and foremost, our research highlights the broader societal implications of social media's pervasive influence. It raises concerns about the emergence of societies fixated on achievement at the expense of personal fulfillment and

relationships, while also promoting conformity that could stifle diversity of thought. By actively contemplating our role in shaping the impact of social media and fostering a healthier relationship with this powerful tool, we can work towards cultivating a sense of self-worth that extends beyond narrow achievements or conforming to the expectations of others. However, it is important to acknowledge that our findings do not necessarily suggest that social media intensifies inherently negative values. Instead, our findings underscore the notion that one specific digital technology could significantly impact our individual values. Typically, values are shaped as a result of an internal journey through exposure to many different cues, personal growth, and societal discourse (Kluckhohn 2013; Rokeach 2008; Schwartz 1992). However, the notion that a digital technology (i.e., social media) which is constructed by commercially driven companies influencing individual values is very intriguing and potentially dangerous. This raises important questions and concerns regarding the manipulation of our values for profit-driven motives.

Second, our research can inform practitioners and educators in designing, implementing, and promoting educational programs that foster critical thinking and healthy habits regarding technology use. By incorporating these programs into educational curricula, we can empower young people to resist the pressure to conform and develop their own unique goals and aspirations. This can contribute to the cultivation of independent thinking, resilience, and the ability to navigate the digital landscape effectively. In addition, policymakers need to take action to prevent social media from exacerbating anxiety and perpetuating the need for approval, particularly among young people. Policy interventions targeting social media features that promote social comparison, reinforce group norms, and heavily personalize user content can help mitigate these negative effects. By implementing measures that promote user well-being and mental health, policymakers can contribute to creating a safer and healthier digital environment.

Finally, the implications of changing individual values extend beyond the realm of personal beliefs and attitudes. As social media plays a significant role in shaping individual values, shifts in these values can have profound effects on individuals' behaviors, decision-making processes, and their interactions within society (Hurst et al. 2013; Kasser et al. 2014; Lee et al. 2022; Pulfrey and Butera 2016). For instance, a shift towards values emphasizing material success and external validation may lead to a culture of hyper-competitiveness and a relentless pursuit of status, potentially at the expense of genuine well-being and interpersonal relationships. Conversely, if social media elicits values centered around empathy, social connectedness, and authenticity, it could foster a more compassionate and inclusive society. These changes in values can influence how individuals perceive societal norms, shape their aspirations, and ultimately impact the broader cultural landscape. Therefore, understanding and addressing the dynamics of value change in the context of social media use is crucial for cultivating a healthy and sustainable society.

Limitations

Our studies have limitations and we acknowledge them in order to provide a comprehensive understanding of the findings. First, a significant limitation concerns the availability of longitudinal data pertaining to social media usage. Since this study aimed to investigate the impact of social media over time, obtaining comprehensive data dating back to the early days of social media posed a challenge. Although data from the European Social Survey (ESS) was accessible from the early 2000s, acquiring consistent and reliable data specifically related to social media usage proved to be difficult. The dataset we used from DataReportal had social media related data as far back as 2014, but not before. As a result, Study 1 relied on the data from the three waves of the ESS (2014-2016-2018) and this longitudinal data had to be supplemented with social media related variables extracted from other sources to capture the desired information.

Another limitation relates to the proxy utilized in Study 1. Given the scarcity of available data on social media, the independent variable in Study 1 was constructed using a combination of country-level social media exposure and individuals' ages that is available in the ESS datasets. While this approach provided a feasible workaround to create an effective independent variable, it is important to acknowledge that the proxy may not fully capture the complexity and nuances associated with social media use. Ideally, more comprehensive and precise measures could have been employed if the necessary data were readily available.

The third limitation pertains to the sample size in the third study. It was observed that certain effects did not achieve statistical significance, likely due to the relatively small sample size. This study encountered challenges with participant attrition rates during data collection, which ultimately impacted the overall sample size. Future research endeavors should strive to secure larger sample sizes to enhance statistical power and increase the robustness of the findings.

In Study 3, we found different patterns of results for achievement and conformity values. The activation of achievement and conformity values by primes (i.e., social media use) might have temporal differences. That is, the value of achievement might be swiftly triggered by the striking salience of social comparisons. For instance, a single post showcasing a friend's seemingly perfect life could instantaneously evoke feelings of achievement. On the other hand, the value of conformity may necessitate a longer duration of exposure to social media (at least, more than five minutes) as the gradually emerging patterns of social norms within a group gradually become salient. However, the evidence to support this suggestion is not in the scope of our findings. Future research can overcome this limitation by also manipulating the amount of exposure to social media in their experimental designs.

Furthermore, the measurement of values, by Schwartz's seminal work, presented a challenge within this study (Schwartz 1992). While the Schwartz values framework serves as

a foundational basis for understanding personal values, it is important to recognize the potential limitations of the measurement scales employed. There may be scope for improvement by introducing additional value dimensions or refining the existing measurement items to more accurately reflect the underlying concepts they aim to capture (in addition to the incremental improvements over the years, e.g., Schwartz et al. 2012; Schwartz 2016). Future investigations could benefit from a thorough evaluation of the measurement items used to assess values and consider potential enhancements or alternative measurement approaches. With that said, investigating people's values and how they might change is inherently a difficult task. Even though we included a broad set of theoretically grounded control variables in our studies, it is difficult to precisely isolate everything that might contribute to shaping individual values.

Directions for future research

Building on our findings and interpretations, we offer potentially fruitful avenues for future research. One promising direction for future research involves examining users who may be particularly vulnerable to the effects of social media. Certain individuals may possess predispositions or specific characteristics (e.g., age, gender, low self-esteem) that render them more susceptible to the influence of social comparisons on social media platforms (Brailovskaia et al. 2023; Forest and Wood 2012; Perloff 2014). Additionally, exploring how major life events, such as breakups, childbirth, or the loss of a loved one, impact individuals' susceptibility to social media effects and potentially influence their personal values could provide valuable insights. Investigating these factors can shed light on the complex interplay between individuals' vulnerabilities, life circumstances, social media usage, and value formation.

Another area of exploration lies in the emergence of social media users who actively challenge the prevalent culture of upward comparisons. These individuals contribute to reshaping social media by sharing authentic moments, engaging in educational content, openly

discussing both lows and highs in their lives, and expressing emotions more openly, without being concerned about maintaining a pristine façade for others. Although such users currently represent a tiny minority, their actions might gradually lead to a potential shift in the future landscape of social media and the corresponding impact on personal values. Future research can investigate the dynamics of these emerging trends, their effects on users' well-being, and the evolving influence of social media on value systems.

In relation to the causal effects we examined in Study 3, future research can further develop and strengthen this causal link by conducting larger-scale experiments in both laboratory and real-world settings. The present study faced limitations in strictly controlling participants' engagement with the requested tasks, despite obtaining post-task summaries of the encountered posts or articles. To address this, innovative approaches such as developing user-friendly applications or browser add-ons can be explored to ensure optimal implementation of experimental manipulations. By employing these technologies, future researchers can enhance experimental control and precision.

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APPENDIX

Table I. Detailed results of Study 1 with robustness checks.

	Gaussian copula approach		Instrumental variable method	
	Achievement	Conformity	Achievement	Conformity
Predictors				
Social Media Penetration [1]	.068 (.022)***	.059 (.021)***	.066 (.025)***	.095 (.024)***
Age	-.015 (.001)***	.009 (.001)***	-.016 (.001)***	.008 (.001)***
SM Penetration X Age **(IV)**	-.001 (.001)***	-.001 (.001)***	-.001 (.001)**	-.001 (.001)***
Gaussian Copula	-.622 (.220)***	-.353 (.211)*	-	-
Instrumental Variable (Alcohol Use)	-	-	-.070 (.030)**	-.091 (.028)
Observations	39420	39275	39420	39275
AIC	120485.550	116358.175	120487.863	116350.653

Correlations between chosen instrumental variable, independent and dependent variables

Variables	(1)
(1) Alcohol Use (Instrumental Variable)	
(2) Social Media Penetration	-0.432
(3) Achievement	0.078
(4) Conformity	-0.046

*** p<.001; ** p<.01; * p<.05. SM= Social Media. AIC= Akaike Information Criterion. IV= Independent variable used in Study 1. Full models with the entire list of controls were used. [1] Potentially endogenous variable.

Table II. List of measurement items and scale evaluations for variables used in Study 2 and Study 3 in the order of presentation.

Variables	Measurement Items	Scale Evaluations	
		Study 2	Study 3
Achievement [1] (Schwartz et al. 2012)	Here we briefly describe some people. Please read each description and think about how much each person is or is not like you. Then choose the best answer that shows how much the person in the description is like you. HOW MUCH LIKE YOU IS THIS PERSON? • He/She* thinks it is important to be ambitious. • Being very successful is important to him/her. • He/She wants people to admire his achievements.	α=.84 CR=.85 AVE=.66	α=.81 CR=.83 AVE=.62
Conformity [1] (Schwartz et al. 2012)	Here we briefly describe some people. Please read each description and think about how much each person is or is not like you. Then choose the best answer that shows how much the person in the description is like you. HOW MUCH LIKE YOU IS THIS PERSON? • It is important to him/her to avoid upsetting other people. • He/She thinks it is important never to be annoying to anyone. • He/She always tries to be tactful and avoid irritating people.	α=.83 CR=.83 AVE=.63	α=.85 CR=.85 AVE=.65
Anxiety [2] (Pilkonis et al. 2011)	How much have you experienced the following in the last week? • I felt fearful. • I felt it was hard to focus on anything other than my anxiety. • My worries overwhelmed me. • I felt uneasy.	α=.93 CR=.93 AVE=.77	α=.94 CR=.95 AVE=.81
Self-rumination [3] (Trapnell and Campbell 1999)	Please indicate how much you agree with the following statements. • I tend to "ruminate" or dwell over things that happen to me for a really long time afterward. • Often I'm playing back over in my mind how I acted in a past situation. • I always seem to be rehashing in my mind recent things I've said or done. • Long after an argument or disagreement is over with, my thoughts keep going back to what happened. I don't waste time rethinking things that are over and done with. (-) • I often reflect on episodes in my life that I should no longer concern myself with.	α=.92 CR=.93 AVE=.68	α=.94 CR=.94 AVE=.72
Need for approval [4] (Rudolph et al. 2005)	Please indicate how much you agree with the following statements. • Being liked by others makes me feel better about myself. • I feel like a good person when others like me. • When others like me, I feel happier about myself. • I feel proud of myself when others like me.	α=.90 CR=.91 AVE=.71	α=.93 CR=.93 AVE=.78
Need to avoid disapproval [4] (Rudolph et al. 2005)	Please indicate how much you agree with the following statements. • When others don't like me, I feel embarrassed about myself. • I feel ashamed of myself when others don't like me. • I feel like I am a bad person when others don't like me. • When others don't like me, I feel down on myself.	α=.94 CR=.95 AVE=.81	α=.95 CR=.95 AVE=.82
Social media use [5]	• How much time do you spend on Facebook on a typical day? (in minutes) • How much time do you spend on Instagram on a typical day? (in minutes) • How much time do you spend on Twitter on a typical day? (in minutes) • How much time do you spend on TikTok on a typical day? (in minutes) • How much time do you spend on Snapchat on a typical day? (in minutes) • How much time do you spend on LinkedIn on a typical day? (in minutes)	–	–
Internet use [6]	How much time (in hours) do you spend on the following activities on a typical day? • Using the Internet (e.g., sending emails, browsing websites, etc.)	–	–

[1] 6-point scale (1-Not at all like me, 6-Very much like me). [2] 5-point scale (1-Never, 5-Always). [3] 5-point scale (1-Strongly disagree, 5- Strongly agree). [4] 5-point scale (1-Not at all, 5- Very much). [5] Measured using a slider from 0 to 600. [6] Measured using a slider from 0 to 1. α=Cronbach's alpha, AVE= Average variance extracted, CR= Composite reliability.

* The pronouns in the measurement items were dynamically adapted to the chosen gender of the participant during the survey.

Table III. Results of Study 2 with Gaussian copula included in the model.

Path		**Full Model**	**[95% CIs]**	
Main links		*Coef. (SE)*		
Social Media Use [H3, φ]	→ Anxiety	-.001 (.001)	-.000	.001
Anxiety [H5]	→ Need for Approval	.094 (.030)**	.035	.153
Anxiety [H6]	→ Need to Avoid Disapproval	.396 (.039)***	.320	.471
Need for Approval [H7]	→ Achievement	.267 (.051)***		
Need for Approval [H9]	→ Conformity	.386 (.045)***	.298	.474
Need to Avoid Disapproval [H8]	→ Achievement	-.058 (.037)	-.130	.013
Need to Avoid Disapproval [H10]	→ Conformity	.095 (.032)**	.032	.157
Interaction effect & Main effects of the moderator				
SM Use X Self-Rumination [H4]	→ Anxiety	.001 (.001)***	.000	.001
Self-Rumination	→ Anxiety	.517 (.028)***	.463	.572
Control paths				
Social Media Use	→ Achievement	.001 (.000)***	.000	.002
Social Media Use	→ Conformity	-.000 (.000)	-.001	.000
Social Media Use	→ Need for Approval	.001 (.000)***	.000	.001
Social Media Use	→ Need to Avoid Disapproval	.001 (.001)	-.000	.001
Gaussian copula	→ Anxiety	.079 (.051)	-.021	.179

*p < .05, **p < .01, ***p < .001; standardized coefficients, SE=Standard Error. [φ] Potentially endogenous variable.

Table IV. Results of Study 2 with instrumental variable included in the model.

Path		**Full Model**	**[95% CIs]**	
Main links		*Coef. (SE)*		
Social Media Use [H3, φ]	→ Anxiety	.001 (.001)	-.002	.003
Anxiety [H5]	→ Need for Approval	.094 (.030)**	.035	.153
Anxiety [H6]	→ Need to Avoid Disapproval	.396 (.039)***	.320	.471
Need for Approval [H7]	→ Achievement	.267 (.051)***		
Need for Approval [H9]	→ Conformity	.386 (.045)***	.298	.474
Need to Avoid Disapproval [H8]	→ Achievement	-.058 (.037)	-.130	.013
Need to Avoid Disapproval [H10]	→ Conformity	.095 (.032)**	.032	.157
Interaction effect & Main effects of the moderator				
SM Use X Self-Rumination [H4]	→ Anxiety	.001 (.001)***	.000	.001
Self-Rumination	→ Anxiety	.517 (.028)***	.463	.572
Control paths				
Social Media Use	→ Achievement	.001 (.000)***	.000	.002
Social Media Use	→ Conformity	-.000 (.000)	-.001	.000
Social Media Use	→ Need for Approval	.001 (.000)***	.000	.001
Social Media Use	→ Need to Avoid Disapproval	.001 (.001)	-.000	.001
Instrumental Variable [1]	→ Anxiety	-.000 (.001)	-.003	.002

Correlations between chosen instrumental variable, independent and dependent variables

Variables	(1)
(1) Browser used by the participant (Instrumental Variable)	
(2) Social Media Use	.165
(3) Anxiety	.064

*p < .05, **p < .01, ***p < .001; standardized coefficients, SE=Standard Error. [1] Instrumental variable was the browser used by the participant. [φ] Potentially endogenous variable.

CHAPTER 5 – CONCLUSION

Across three essays, this dissertation explores the multifaceted realm of human-technology relationships, with a particular focus on exploring the potential dark sides that coexist alongside the benefits. As technology continues to play an increasingly pervasive role in our lives, it becomes imperative to gain a comprehensive and balanced understanding of its impact. With my research, I seek to contribute to this understanding by shedding light on the intricate dynamics of human-technology interactions, emphasizing the need to go beyond surface-level analysis and delve deeper into the potential implications.

Essay 1 investigated the phenomenon of anthropomorphism in AI, exploring its effects and shedding light on its nuanced nature. Through a systematic literature review, we presented two contrasting streams of thought. One stream, grounded in anthropomorphism theory (Epley et al. 2007), suggests that anthropomorphism in AI has positive effects. However, the other streams, relying on uncanny valley theory (Mori et al. 2012) or expectation confirmation theory (Oliver 1980; e.g., Nowak and Biocca 2003), argue for negative consequences. To reconcile these inconsistent findings, we conducted a three-layer analysis. In the first layer, we explored the contrasting theoretical perspectives to gain a comprehensive understanding of the effects of anthropomorphism in AI. We propose that by combining these different theoretical perspectives and moving beyond a limited analysis based on a single theoretical lens, we can fully uncover the implications of anthropomorphism. In the second layer, we explored the role of contextual factors in determining the effects of AI anthropomorphism. Finally, in the third layer, we investigated the influence of individual characteristics on the effects of AI anthropomorphism.

Our review encompassed a broad body of empirical work from different disciplines, enabling us to provide novel insights for future research in marketing and consumer behavior. Importantly, we found that the potency of AI anthropomorphism is contingent upon contextual and individual characteristics. Additionally, we proposed that understanding the interactions between humans and anthropomorphized AI entities from a relationship perspective could yield valuable insights because attributions of a mind to such entities exist relative to our own minds and could evoke an experience of a relationship.

Essay 2 centered around the impact of anthropomorphism in AI assistants on consumer well-being and privacy. Through two studies, we uncovered the two-sided effects of anthropomorphism. The first study demonstrated that higher perceived anthropomorphism increased consumer satisfaction by fostering trust in the AI assistant, a result that echoes previous work (e.g., Foehr and Germelmann 2020; Li and Sung 2021; Pitardi and Marriott 2021). However, our findings went beyond the benefits, revealing psychological costs for consumers. Specifically, a stronger perception of anthropomorphism heightened privacy concerns through increased identity threat. Notably, these harmful effects were more pronounced for consumers with longer and closer relationships with the AI assistant. Furthermore, we examined the effectiveness of intervention strategies in mitigating the negative impact of identity threat on consumer empowerment. In particular, prompting consumers to take action about their privacy in their relationship with the AIA (the third intervention in Study 2) had the most marked effect. The results underscored the importance of managing privacy concerns to enhance user empowerment and well-being. Overall, this research highlights the need for a relationship perspective in understanding consumer-AI interactions, while also providing actionable insights for marketing managers to navigate the complexities of AI anthropomorphism, prioritize consumer well-being, and optimize consumer experiences.

Essay 3 explored the intricate influence of social media on individual values, achievement and conformity (Schwartz 1992). Across three studies, our investigation utilized a comprehensive methodology involving longitudinal data analysis, a large consumer survey, and an experiment to provide robust insights into this phenomenon. In the first study, we conducted an analysis of longitudinal data from the European Social Survey, involving a substantial sample size of approximately 80,000 individuals. Our findings revealed that a greater social media exposure led to an increase in values of achievement and conformity. We argued that individuals strive to strike a balance between belonging to a social group and asserting their distinctiveness within that group by getting ahead (Brewer 1991). Social media platforms amplify this process to an unprecedented degree, leading to a notable rise in people's inclination towards achievement and conformity values.

To validate and expand upon these initial findings, we conducted Study 2, a large-scale consumer survey involving 1,000 participants. The results of this survey not only replicated our previous findings but also shed light on the underlying mechanisms. We discovered that social media use contributes to increased achievement and conformity values through heightened levels of anxiety and the need for approval. These psychological factors act as mediators, shaping individuals' value systems in response to their social media engagement. Furthermore, in a third study, we employed an experimental approach to manipulate social media exposure and examine its immediate effects on individual values. Our results demonstrated that even brief exposure to social media activated achievement and conformity values in users. We argue that repeated exposure to social media multiple hours every day, as is typical with millions of people, could lead to permanent changes in values. This experimental manipulation provided further evidence for the influential role of social media in fostering a societal culture that places a strong emphasis on achievement-seeking and conformity.

Theoretical Contributions And Future Research

This dissertation makes a valuable contribution to the understanding of human-technology relationships within the realm of intelligent technologies and social media. Specifically, Essay 1 focuses on the use of anthropomorphism in AI, a widespread practice observed in contemporary gadgets such as AI assistants like Alexa and even ChatGPT. By offering a concise framework and advocating for a broader theoretical perspective, it enriches the existing literature on anthropomorphism in AI (e.g., Epley et al. 2007; Mori et al. 2012; Yang et al. 2020). This essay underscores the importance of exploring the effects of anthropomorphism in AI and provides insights into this prevalent phenomenon in the new technological landscape.

Building upon the framework proposed in this work, there are several promising directions for future research. First, it is crucial to explore the effects of AI anthropomorphism in broader theoretical frameworks that incorporate both positive and negative outcomes. Integrating theories such as techno-stress, psychological strain, and consumer ambivalence can provide a more balanced perspective on the implications of anthropomorphism in AI (Ayyagari et al. 2011; Edwards 1996; Otnes et al. 1997). Moreover, it might be pertinent to seek updated theories or even build new theoretical frameworks on the psychology of technology. Most of the established theoretical models to explore human-technology relationships are decades old (e.g., Davis et al. 1989). Even though they are occasionally updated to account for latest technologies or consumer behaviors (e.g., Abdullah and Ward 2016; Shih 2004), we should remember that the role of technology in people's lives are expanding exponentially. Perhaps, a fundamental shift in perspective is necessary on how we view technology, and sometimes this shift is compelled upon us as we see with large language models like ChatGPT.

Essay 2 makes a notable contribution to the literature that advocates for a balanced examination of the role and impacts of technology in our lives, going beyond the narrow focus on its benefits (e.g., Cukier 2021; Puntoni et al. 2021). Building upon the insights presented in Essay 1, Essay 2 provides empirical evidence that highlights the presence of both the beneficial

and harmful effects within the same conceptual framework. Furthermore, Essay 2 expands upon the notion proposed at the end of Essay 1, emphasizing the significance of adopting a relationship perspective when exploring human-technology interactions. It presents empirical evidence on the relationships consumers form with AI assistants and sheds light on the consequences of these interactions for consumers. This notion of taking a relationship perspective not only carries practical implications but also holds theoretical relevance as it can guide future investigations into the ever-increasing array of technologies people engage with on a daily basis.

In light of the insights offered in Essay 2, there are several compelling directions for future research. First and foremost, there is immense potential in adopting a relationship perspective to explore human-technology interactions. While this perspective has not been exploited by extant research so far, drawing inspiration from relationship marketing theories (e.g., Dwyer et al. 1987; Jap and Ganesan 2000; Zhang et al. 2016) to investigate human-technology relationships holds great promise for future research endeavors. By examining human-technology relationships through this lens, researchers can delve deeper into the dynamics, trajectories, and evolving nature of these relationships over time. This shift in focus would allow us to transcend the view of technology as a mere convenience gadget or data collector, and instead uncover the multifaceted ways in which technology connects with humans.

Furthermore, future research should expand the scope of inquiry to encompass the broader implications of different technologies and our relationships with them. It is crucial to examine how the benefits and harms associated with various technologies influence our overall perception of technology and shape our attitudes towards its adoption. By conducting comprehensive studies that explore the nomological network of consumers' relationships with technology, future research can unravel the antecedents, mechanisms, outcomes, and strategies

to address concerns related to consumers' human identity and the potential displacement of human tasks by AI. Such research can guide marketers, policymakers, and society as a whole in navigating the evolving landscape of technology with wisdom and foresight.

Essay 3 makes several significant theoretical contributions to our understanding of the impact of social media on individual values and behaviors. First, it explores dynamics of social groups within social media platforms and their influence on individuals' social identities. By showing that people seek approval and conformity with their social group's norms and values, the study highlights the role of social comparison and the need for approval in shaping individual behavior. This advances the knowledge on the mechanisms through which social media impacts individuals (e.g., Ki and Kim 2019; Luo and Hancock 2020; Zhan et al. 2016). Second, Study 2 in this essay introduces self-rumination as a moderator for the effect of social media on anxiety. This novel moderator provides insights into how individuals' tendencies to ruminate about themselves can amplify the impact of social media-induced anxiety. Overall, this research expands our knowledge of the psychological effects of social media and contributes to the broader literature on the relationships between technology use and digital well-being (Benvenuti et al. 2023; Lima and Belk 2022; Monge Roffarello and De Russis 2019).

Building upon the findings of this study, there are important avenues for future research. First, investigating how the shifts in values manifest over time and their consequences on personal fulfillment, relationships, and societal well-being would provide a more comprehensive understanding of the societal impact of social media. Additionally, further research could delve into the underlying mechanisms through which social media influences individual values, such as examining the role of specific features or algorithms in promoting social comparison and reinforcing group norms.

Practical Implications

The findings of Essays 1 and 2 have practical implications for the use of anthropomorphism in AI. Future research should investigate the nonlinear effects of anthropomorphism, considering that its impact may vary depending on the specific context and tasks carried out by AI agents. It is crucial to carefully assess the suitability of anthropomorphism in AI rather than employing it arbitrarily, taking into account whether it aligns with the customer journey and the stage of the relationship with AI. Integrating relationship theories and exploring the trajectories and efficacy of anthropomorphism in different relationship stages offer a novel lens for investigation. Additionally, individual characteristics of AI users, such as age, gender, cultural differences, and personality traits, should be systematically considered to better understand the role of AI anthropomorphism perception. Designers of anthropomorphic features should be mindful of their congruence with the use context and users' expectations, ensuring the implied affordances align with user preferences and needs. Investigating the nonlinearity in how individuals respond to different levels or combinations of anthropomorphic features in different contexts can provide valuable insights into understanding the nuanced effects and optimizing the design of anthropomorphized AI agents.

Essay 2 suggests that managers have a unique opportunity to empower their customers while still benefiting their firm. In Essay 2, we tested simple yet effective intervention strategies that inform and encourage consumers to take action in protecting their data privacy. These strategies, such as providing information about data practices and privacy preferences, can enhance consumer relationships with various technologies. Moreover, the potential for empowerment strategies to further empower consumers is vast. Future research can explore more advanced and tailored approaches to empower consumers, considering individual characteristics, preferences, and specific contexts. By leveraging the capabilities of AI and technology, managers can develop personalized interventions that go beyond basic information provision. For instance, interactive AI agents can engage in meaningful conversations to

educate users about privacy and provide real-time guidance on protecting their data. Advanced empowerment strategies can empower consumers not only in managing data privacy but also in making informed decisions, navigating digital platforms, and asserting control over their technological experiences. Our research lays the foundation for these innovative empowerment strategies and represents the first step towards enabling consumers to take an active role in their relationships with technology.

Essay 3 suggests that understanding the mechanisms through which social media impacts its users can inform the design of interventions and policies aimed at promoting healthier social media use. Future studies could explore the effectiveness of different educational programs and interventions in mitigating the negative effects of social media, fostering critical thinking, and empowering individuals to resist conformity pressures. By addressing these future research directions, we can deepen our understanding of the complex interplay between social media, values, and well-being and contribute to the development of strategies that promote healthier digital environments for individuals and society as a whole.

Limitations

In this section, a summary of the broader limitations associated with the topic of this dissertation is provided, rather than reiterating the specific limitations discussed in each individual essay.

The rapid advancement of technology poses a challenge to the generalizability and applicability of our findings on anthropomorphism. As new technologies with increasingly human-like abilities emerge, such as ChatGPT, the conversations and dynamics surrounding anthropomorphism may undergo significant transformations. While our current insights on anthropomorphism remain relevant, it is essential to acknowledge that the field is evolving at a rapid pace, and the implications presented in this work may require updating in the future.

Another limitation stems from the current state of technology itself, which affects our studies and findings. Although we have demonstrated the anthropomorphism in AI assistants and the formation of relationships with them, the quality of spoken interaction with these technologies is still far from flawless. Future technological advancements will likely enhance the capabilities of AI assistants and similar technologies, making this topic even more relevant. While we are limited by the capabilities of current technologies in our empirical work, our theoretical implications may continue to hold value in the coming years.

In the context of social media, disentangling the long-term effects of these platforms presents a significant challenge. While we have demonstrated the short-term effects through manipulations in Study 3 of the third essay, understanding the enduring impact of social media on individuals requires comprehensive data spanning from the inception of social media's integration into our lives. However, the lack of detailed data on social media use during the earlier stages of its introduction limits our investigation. Exploring the initial steps of change in individuals and society as a result of social media's arrival remains an intriguing area, but it is constrained by the availability of historical data.

These limitations highlight the dynamic nature of technology and the need for ongoing research and updates to capture the evolving landscape accurately. As technology continues to progress, it will be essential to adapt our methodologies and investigations to stay relevant and gain deeper insights into the complex interactions between humans and emerging technologies.

In conclusion, I hope that the three essays of my dissertation contribute to the advancement of knowledge in this area, with both theoretical and practical implications. As a young researcher, it has been enjoyable to work on a topic that directly relates to my everyday life and personal experiences.

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