FAR BEYOND MACHINES?

AN EXPERIMENTAL STUDY OF IF AND HOW HUMANLIKE TECHNOLOGY DESIGN AND ANTHROPOMORPHISM IMPACT CONSUMER PERCEPTIONS OF AUTONOMOUS VEHICLES

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Far beyond machines? An experimental study of if and how humanlike technology design and anthropomorphism impact consumer perceptions of autonomous vehicles

Abstract:

Autonomous technologies' widespread emergence makes it vital for technology producers and marketers to understand how to enhance human–technology interactions that can drive consumer preferences. However, research in this area is fragmented and inconsistently applied in practice. This study examines whether and how humanlike technology design (a.k.a. technology humanization) and anthropomorphism influence consumer perceptions of autonomous vehicles. A between-subjects experiment, based on a comprehensive theoretical model, examined the chain of effects between humanization, anthropomorphism, product attitudes, and intentions to use. The results revealed minor effects of humanization on anthropomorphism, fully mediated by perceptions of warmth. Anthropomorphism had a moderate influence on product attitudes, partially mediated by emotional valence and cognitive trust. Overall, the findings suggest that technology humanization does not significantly impact consumers' attitudes or intentions to use autonomous vehicles, as anthropomorphism primarily stems from other antecedents. While anthropomorphism influences consumer perceptions to some extent, it appears largely beyond the control of makers or marketers of autonomous technologies.

Keywords:

Anthropomorphism, technology humanization, humanlike technology design, autonomous technology, autonomous vehicles, human-robot interactions

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1. Introduction

Autonomous technologies are rapidly emerging as natural parts of our daily lives. This compels us to rethink our relationship to technology, as it evolves from being tools under our control – to something that we need to trust. And few autonomous technologies will require our trust and confidence more than self-driving cars. Imbuing technology with humanlike design to inspire *anthropomorphism* – a psychological process where consumers perceive technology as possessing human qualities – is widely applied to make technology more understandable, relatable, and trustworthy. While supported by theory and a vast number of empirical studies, research in this area is fragmented and such strategies are rarely used in practice by car manufacturers. Consequently, the effects of these processes on consumer perceptions remain unclear.

Understanding the dynamics of human–technology interactions is vital for producers and marketers of autonomous technologies aiming to shape consumer preferences and behaviors. Addressing this research gap, this thesis examines if and how humanlike technology design and anthropomorphism impacts consumer attitudes towards autonomous vehicles, and its implications on subsequent intentions. To achieve this, the study draws on existing theory and prior findings to develop a framework examining the full chain of effects of humanlike technology design and anthropomorphism on dependent variables essential to autonomous technology makers and marketers. The resulting framework is then tested in a quantitative between-subjects experiment.

This introduction presents the thesis' background, identified problem area, research gap, purpose, research question, delimitations, and expected contribution. The next section accounts for the study's theoretical framework, grounded in a detailed literature review, which informs the study hypotheses. The third section describes the methodology and provides credibility to the results presented in the fourth section. Finally, the discussion and conclusion examine the findings in relation to existing theory and studies, explore theoretical and practical implications, and offer suggestions for future research.

1.1. Background

There are many indications that our human relationship with technology is changing. For many of us, rapid technological advancements have made voice assistants, generative AI, and household robots' natural parts of our daily lives. Even today, some of us trust self-driving cars to drive our families through dense traffic at maximum legal speeds. Meanwhile, research on autonomous technology and artificial intelligence is exploding. The 48 460 articles written during the past five years almost tripled the total number of articles on the subject (Scopus, 2024). The widespread emergence of

autonomous technology prompts us to reexamine how we relate to it, as relinquishing control to autonomous technological entities demands an entirely new level of trust.

From a marketing perspective, it is critical to be able to influence the drivers of consumers' autonomous technology adoption. One such potential driver, *technology humanization* – the act of imbuing technology with human-like design – is widely used to make technology more relatable and enhance human–technology interactions (Blut et al., 2021; Erebak & Turgut, 2019; Salem et al., 2013; W. Zhang et al., 2024). Humanization is common among voice assistants (e.g., Siri, and Alexa) but less explicit in GenAIs such as ChatGPT, which has a technological name but communicates by simulating human dialogue and empathy (Welivita & Pu, 2024). This phenomenon also extends to non-autonomous technologies: even the regular dishwasher "Bob" has found success by being marketed as a person (Kamps, 2022). Autonomous vehicles, however, are rarely humanized. For instance, Tesla's recent robot taxi prototype notably removed the car's voice in favor of a limited interface that asked passengers what entertainment they would like to stream after they selected their destination (Auto Focus, 2024).

One goal of technology humanization is commonly to inspire *anthropomorphism,* a psychological process where consumers attribute human traits, emotions or intentions to non-human entities to make them more understandable or relatable by regarding them as social beings (Epley et al., 2007; Epley, 2018). Many empirical studies indicate that anthropomorphism positively impacts consumer perceptions of technology, for instance, by increasing trust (de Visser et al., 2016; Feng et al., 2024; J.-C. Lee & Chen, 2022; van Pinxteren et al., 2019; Waytz et al., 2014), liking (Stroessner & Benitez, 2019; Waytz et al., 2014), and perceived service quality (Söderlund, 2022). However, anthropomorphism can result from multiple antecedents, including personal characteristics and socio-cultural contexts (Epley et al., 2007; Blut et al., 2021) – and humanization is thus not any guarantee for anthropomorphism. Nevertheless, given the strong support for anthropomorphism's positive effects on consumers' perception of autonomous technologies, this creates the question: why aren't self-driving cars extensively humanized to inspire anthropomorphism which is claimed to positively influence consumer preferences and technology adoption?

1.2. Problem area and research gap

Despite the existence of a foundational and widely cited theory on the psychological mechanisms underpinning anthropomorphism (Epley et al., 2007), research on the effects of humanization and anthropomorphism remains fragmented. Many empirical studies focus on how personal determinants or socio-cultural contexts influence anthropomorphization (e.g., H. Y. Kim & McGill, 2018; S. Kim & McGill, 2011; Wan, 2018) or examine the outcomes of anthropomorphic processes that have already occurred (Alain Goudey, 2016; Q. Q. Chen & Park, 2021; Cui, 2022; Gursoy et al.,

2019; Lu et al., 2019; Pillai & Sivathanu, 2020; H. Qiu et al., 2020). However, these studies offer limited practical value for marketers or makers of autonomous technologies, as consumers' personal traits, social contexts, or prevailing cultures are challenging – if not impossible – to influence or control on a global market.

Furthermore, while several studies explore the impacts of technology humanization on anthropomorphization (e.g. Erebak & Turgut, 2019; Salem et al., 2013; Waytz et al., 2014; Zhang et al., 2010) inconsistent measures prevent meaningful comparisons (Bartneck et al., 2009). And rarely do such studies extend their scope to include dependent variables crucial for affecting consumer behavior, such as product attitudes. Even Waytz et al.'s (2014) seminal study on humanization and anthropomorphization of autonomous vehicles highlights beneficial effects on consumers' trust and liking of AVs, without assessing the impact on consumers' overall preferences towards self-driving cars. Despite anthropomorphism's growing relevance, its downstream impacts remains "unfortunately underexplored" (Cui, 2022). Consequently, it is unclear to what extent technology humanization inspires anthropomorphism, and if anthropomorphism ultimately benefits consumer preferences by shaping attitudes that can drive behavior.

1.3. Purpose and research question

In summary, as autonomous technologies are emerging as vital parts of our daily lives, it is essential for marketers and technology developers to fully understand the dynamics of human–technology interactions that can enhance consumer preferences and drive technology adoption. Given the fragmented research on the effects of humanization and anthropomorphism – which are often claimed to enhance such interactions – this thesis' purpose is to provide insights into how technology humanization influences anthropomorphism, and how anthropomorphism subsequently shapes consumer perceptions vital for marketers and producers. The research question is therefore:

Does human-like technology design and anthropomorphism impact consumer perceptions of autonomous vehicles – and if so, how?

1.4. Delimitations

Several delimitations were made to ensure the study's feasibility. From the broader category of autonomous vehicles, self-driving cars were selected due to their nascent status (Derek Chiao et al., 2024; Wilhelm, 2023) and because cars are widely regarded as high-involvement and transformational (i.e., emotional) purchases (Rossiter et al., 1991). If humanization and anthropomorphism can foster trust, reduce perceived risks, and evoke positive emotional valence, this could significantly encourage AV adoption. This makes it particularly interesting why humanization is not widely applied to self-driving cars and motivates the study's focus. Nevertheless, the findings aim to offer

insights relevant for AVs in general, which can extend to more product categories involving autonomous technologies.

The study is further delimited to technology humanization as the primary antecedent of anthropomorphism. It excludes personal determinants, other background variables, or moderators, as such factors are difficult to influence and thus offer limited practical value. The experiment design was governed by the study's scope and resources and is described in detail in section 3. Key delimitations include the use of a vignette study instead of alternative stimuli and the use of self-reported measures instead of behavioral ones. Alternative approaches were either beyond available resources or deemed unlikely to add significant value to the experiment under its constraints. Finally, sampling was limited to residents in the U.K., which may affect generalizability.

1.5. Expected contribution

This thesis aims to contribute to the understanding about whether and how technology humanization and anthropomorphism influence consumer perceptions of autonomous vehicles and autonomous technology in general. Addressing the fragmentation of existing research, the study seeks to advance theoretical knowledge by leveraging established theories and studies to construct a framework that maps the full chain of effects – from humanization to anthropomorphism to downstream variables that ultimately shape consumer attitudes and technology adoption. By incorporating all these variables into one single model, the study aims to provide insight into their relative effects when considered collectively, furthering the understanding of their potential impact in practical contexts. The resulting model is hopefully a valuable first step towards establishing a more holistic understanding of these phenomena. Furthermore, as the model is grounded in established theories and measures, it is compatible with existing research with the hope of being both practical and inspiring for future studies.

From a practical perspective, this study hopes to generate insights benefiting both producers and marketers of autonomous technologies. Focusing on humanization – a controllable antecedent to anthropomorphism – allows the findings to inform technology design decisions and marketing strategies about what can be done to inspire anthropomorphism, and what outcomes this could bring. Since the study model tests variables sequentially before assessing them as a whole, a detailed understanding of what aspects of humanization and anthropomorphism influence key outcomes is provided. The findings could help companies prioritize resources to target areas with the greatest potential impact on consumer attitudes and technology adoption. Although this study's primary focus is self-driving cars, the findings should also be relevant for autonomous technologies across multiple industries. Ultimately, the study hopes to offer actionable knowledge about if and why humanization and anthropomorphism matters for creating more relatable and successful autonomous technologies.

2. Theoretical framework and hypotheses

This section describes the thesis' theoretical framework and how it relates to relevant theories and past empirical results. The study's hypotheses are presented in the order of the theoretical model, and the resulting theoretical framework provides the foundation for the study's discussion. First, section 2.1 introduces the theory of anthropomorphism, and presents humanization as a potential antecedent of multiple processes which can inspire anthropomorphism. Second, section 2.2 considers anthropomorphism's potential outcomes and possible effects on consumers' attitudes. Finally, The Theory of Planned Behavior is examined as a potential link between consumers' product attitudes and intentions. Constructed from the theoretical framework, the study's hypotheses and variables were adapted from multiple theories with the intent of examining the full effects of humanization and anthropomorphism on product attitudes and intentions.

Literature was accessed through Scopus, the SSE Library, and Google Scholar. A structured literature search prioritizing peer-reviewed articles according to their number of citations was used to establish the theoretical framework. Keywords for the search included: anthropomorphism, technology humanization, humanlike technology design, autonomous technology, autonomous vehicles, and human-robot interactions. Furthermore, Scopus was used to analyze the references and citations of articles found relevant for the study, leading to the discovery of additional significant material.

2.1. Anthropomorphism

Never trust anything that can think for itself if you can't see where it keeps its brain.

While the fictional advice of J.K Rowling (1998) reflects the skepticism many feel towards nonhuman entities – people often do the opposite. The cause for this behavior is anthropomorphism, the psychological process (Wan, 2018) wherein humans "perceive humanlike traits in nonhuman agents" (Epley, 2018). Such perceived traits can be physical, such as in embodiment, or nonphysical such as emotionality or cognitive capabilities (Blut et al., 2021; Epley et al., 2007). People make inductive inferences based on the perceived behavior or appearance of nonhuman entities (Blut et al., 2021; Waytz et al., 2014). In other words, people interpret the behavior of nonhuman entities as being motivated by human intentions (Epley et al., 2007). Humans use their own mental states as a guide to infer the mental and emotional states of nonhuman entities. This is referred to as elicited agent knowledge (Epley et al., 2007). The use of own mental states as a guide to infer mental states about others applies broadly to nonhuman entities including animals, deities, and even technological devices (Epley et al., 2007). Therefore, it is assumed that empirical findings about anthropomorphism in other nonhuman entities can be applied to autonomous vehicle studies.

To perceive mental states in nonhuman entities to begin with, there has to be a perceived mind and mental state within the entity (Epley, 2018; Epley et al., 2007; Söderlund, 2022, 2024a) – it must be seen as more than an object. The capability of humans to perceive mental states in others is referred to as the theory of mind (Baron-Cohen, 2012; Epley, 2018; Epley et al., 2007; Kidd & Castano, 2013; Langley et al., 2022; Söderlund, 2022, 2024a). Although mostly studied in relation to other human beings, the theory of mind has proved relevant in nonhuman studies too (Söderlund, 2022, 2024a). People make inductive inferences about nonhuman behavior motivated by effectance and sociality needs (Epley, 2018). Combined with elicited agent knowledge, these three psychological determinants affect how much people will anthropomorphize a nonhuman entity. Effectance is the motivation to understand and minimize uncertainties in one's environment and the behavior of agents. Sociality is the human need to engage with other humans through social connections. When this need is high, people are more likely to perceive humanlike traits in nonhuman entities (Epley et al., 2007). Nonhuman entities can thus be perceived as social beings (Epley, 2018; Epley et al., 2007; J. Kim et al., 2019; Nass et al., 1994). Cultural differences, however, affect the motivation of sociality. For instance, it's suggested that the tendency to anthropomorphize is higher in people from individualistic cultures (Epley et al., 2007).

It has been theorized (Epley et al., 2007) and shown (Aggarwal & McGill, 2007) that interactions with humanized products are similar to interactions with other human beings. Research also shows that through anthropomorphism, nonhuman entities are evaluated more positively (Q. Q. Chen & Park, 2021; de Visser et al., 2016; J.-C. Lee & Chen, 2022; Li & Sung, 2021; Moussawi et al., 2021; Pillai & Sivathanu, 2020; H. Qiu et al., 2020; L. Qiu & Benbasat, 2009; Schreiter et al., 2022; Söderlund, 2022; Söderlund et al., 2021; Söderlund & Oikarinen, 2021; van Pinxteren et al., 2019; Wan, 2018; Waytz et al., 2014; Youn & Cho, 2023). Conclusively, marketers should consider that anthropomorphism can elicit positive associations with their product (Waytz et al., 2014; W. Zhang et al., 2024).

2.2. Humanlike technology design as an antecedent to anthropomorphism

Often known as humanization, humanlike technology design aims to imbue technology with human-like features with the intent of inspiring anthropomorphism (Araujo, 2018; Blut et al., 2021; Castro-Gonzalez et al., 2018; Epley, 2018; Epley et al., 2007; L. Qiu & Benbasat, 2009; Valenzuela & Hadi, 2017; Waytz et al., 2014). There are mainly two antecedents of anthropomorphism – consumer dispositions and product design features (Blut et al., 2021). Design features that increase the perception of a humanlike mind and mental cognition contribute the most to anthropomorphism (Epley, 2018). For instance, morphological similarities such as facial features, gaze, voice and gender contribute to this perception. Elicited agent knowledge (section 2.1) is driven by egocentric

reasoning, but it can be guided by human-like design cues (Epley, 2018). Physical and behavioral similarities increases the likelihood of people projecting their understanding of themselves onto the nonhuman agent (Blut et al., 2021). Furthermore, people prefer anthropomorphized products that elicit a human gender schema that is congruent with their own gender (Hende & Mugge, 2014). However, research also show that female design cues that elicit warmth and concern are often preferred over male design cues that elicit dominance and authority (Blut et al., 2021; Stroessner & Benitez, 2019; ter Stal et al., 2020). Hence, the context where the nonhuman entity is deployed is influential on humanized design preference (Eyssel & Hegel, 2012; J. Kim et al., 2019).

Consumer dispositions are beyond marketers' control. Humanization of design cues will not lead to the same degree of anthropomorphism in everyone (Waytz et al., 2014). Sociodemographic factors influence the degree that people anthropomorphize (Blut et al., 2021). Thus, it is possible that human design cues have no effect – or even a negative impact – on anthropomorphism. Several ways in which anthropomorphism is induced through technology design are explored in the following sections.

2.2.1. Perceived competence

Perceived competence relates to perceived ability, such as intelligence and skill, and is part of the stereotype content model (SCM; Fiske et al., 2002, 2007). This model suggests that in first encounters with other social beings, humans need to judge whether the being is hostile or friendly – and whether they are capable of acting on these intentions (Carpinella et al., 2017; Fiske et al., 2007). Competence refers to this very capability. It is similar to perceived intelligence (Bartneck et al., 2009; Carpinella et al., 2017), but concerns the ability to act on such intelligence. Through humanized design elements, the AI interface of autonomous vehicles can display competence through social cues. For instance, vocal statements explaining route adaptations, increase the likelihood that the vehicle is evaluated as competent (Epley, 2018; Epley et al., 2007; Waytz et al., 2014). Furthermore, research shows that humanlike robots have been perceived as more competent (Carpinella et al., 2017).

***H1a*:** Technology humanization positively influences perceived competence

Perceived competence suggests the capacity of other human-like qualities, such as intentionality and goal orientation. Thus, the entity might be perceived to have a mind, which increases the perceived humanness (Epley, 2018; Epley et al., 2007). The SCM (Fiske et al., 2002, 2007) suggests that people in the same social group as oneself are seen as more competent and warm. Since people within the ingroup are more similar to the self (Demoulin et al., 2009; Epley et al., 2008; Leyens et al., 2000), it is plausible that nonhuman entities perceived as competent are viewed as more like oneself. Furthermore, similarity enables elicited agent knowledge which increases perceived humanness (Epley, 2018; Epley et al., 2007; see section 2.1). Empirically, perceived

intelligence has also been shown to positively influence anthropomorphism (J.-C. Lee & Chen, 2022; Moussawi et al., 2021).

H2a: Perceived competence positively influences perceived humanness

2.2.2. Perceived agency

Perceived agency in nonhuman entities implies that they possess morality, emotion recognition, and planning abilities (H. M. Gray et al., 2007). In mind perception theory (H. M. Gray et al., 2007), agency is a key component of perceiving others as having a mind. Mind perception theory is similar to the theory of mind (Baron-Cohen, 2012), as both describe aspects of mind attribution. Research show that products designed to be more human have been afforded greater agency (H. Y. Kim & McGill, 2018). However, in Kim & McGill's study (2018), agency was moderated by personal socioeconomic factors, suggesting that personal dispositions might reverse the positive influence of humanized design on perceived agency.

H1b*:* Technology humanization positively influences perceived agency

Gray et al. (2007) tested which beings would be accredited agency, finding that women and oneself were judged as having the most agency. Therefore, if technology is perceived to have agency, it is reasonable that it will be perceived as more human. This has empirical proof for virtual agents (Söderlund & Oikarinen, 2021). Furthermore, when people are dehumanized, wherein people are thought of as less human, moral agency is a key trait perceived as missing (Epley et al., 2007). This suggests that possessing agency signals a high degree of humanness, blurring the distinction between humans and machines (Müller et al., 2021).

H2b: Perceived agency positively influences perceived humanness

2.2.3. Perceived warmth

Perceived warmth is about perceiving traits such as friendliness, helpfulness and sincerity in nonhuman agents (Fiske et al., 2007). Warmth is the emotional preference for an agent (J. Kim et al., 2019). Like competence, it is part of the SCM (Fiske et al., 2002, 2007). Judgments about warmth have primacy over competence. It's more important for humans to determine whether someone has friendly or hostile intentions, rather than if they have the competence to act on those intentions (Carpinella et al., 2017; Fiske et al., 2007). Thus, it can be expected that warmth has a stronger positive effect on perceived humanness and consumer behavior. Perceived emotionality (Söderlund & Oikarinen, 2021) is assumed to be a prerequisite for warmth in nonhuman entities. Warmth reflects the positive intent of an entity (Fiske et al., 2007), meaning that the entity must first be seen as capable of experiencing emotions. Through humanized design, autonomous vehicles can display both emotionality and positive

intent through friendly facial expressions on the AI interface. Accordingly, humanized design features could enhance perceived warmth. Empirical findings align with this argument, showing that humanlike features were perceived as warmer than machinelike features (Carpinella et al., 2017; Stroessner & Benitez, 2019; Hsieh & Lee, 2024). Furthermore, feminine humanlike features evoke more perceived warmth than masculine features (Carpinella et al., 2017; Stroessner & Benitez, 2019).

H1c*:* Technology humanization positively influences perceived warmth

The SCM (Fiske et al., 2002, 2007) suggests that people in the social ingroup have the highest perceived warmth and competence. For instance, An AI referred to as a friend was perceived as warmer compared to one being referred to as a servant (J. Kim et al., 2019). It's been suggested people are more likely to anthropomorphize robots perceived as ingroup members (Carpinella et al., 2017). Thus, if warmth can be elicited, it is plausible that nonhuman entities will be perceived as more human because they're seen as belonging to the ingroup. Therein, they might also be seen as similar to oneself. Similarity, as mentioned before, is a key determinant of anthropomorphism as people rely more heavily on egocentric knowledge in regards to nonhuman agents similar to the self (Epley, 2018; Epley et al., 2007). The argument is strengthened by evidence of the inverse effect where people outside one's social group are frequently dehumanized, i.e. seen as less human (Demoulin et al., 2009; Leyens et al., 2000).

H2c: Perceived warmth positively influences perceived humanness

2.2.4. Perceived morality

Morality can be summarized as the ability to determine what's right from what's wrong and proceeding to do the right thing (H. M. Gray et al., 2007). It is central to what humanness is (Goodwin et al., 2014; Haslam, 2006; Söderlund & Oikarinen, 2021). Nonhuman entities with perceived morality are seen as capable of ethical decisions. It is proposed that humanlike design can enable an autonomous vehicle to display capability of ethical choices. The vehicle can be designed to express statements, through voice, indicating that it prioritizes the safety of humans over other matters. Moreover, Morality is sometimes seen as a display of agency (Pitardi et al., 2021) and warmth (Fiske et al., 2002, 2007). Thus, design features that evoke a perception of mind and friendliness are likely to increase perceived morality as well. There is thus reason to believe that technology designed with human features will be perceived as capable of morality.

H1d*:* Technology humanization positively influences perceived morality

Nonhuman entities perceived as having morality are likely to be perceived as more human, as morality is a core human trait (Goodwin et al., 2014; Haslam, 2006; Söderlund & Oikarinen, 2021). Past empirical results also suggest that humans are capable of accusing computers of lying and deception (Ferdig & Mishra, 2004),

suggesting that computers are believed to have the morality to distinguish between right and wrong. It's also been shown that when people ascribe morality to virtual entities, they're perceived as more human (Söderlund & Oikarinen, 2021). Additionally, groups and individuals seen as lacking morality are viewed as less human, which suggests that having morality is associated with perceived humanness (Haslam, 2006).

H2d: Perceived morality positively influences perceived humanness

2.2.5. Perceived creepiness

Perceived creepiness entails feeling disturbed, eerie, or uncomfortable when interacting with nonhuman entities (K. Gray & Wegner, 2012; Mara et al., 2022; Mori et al., 2012). The phenomenon has been described by the uncanny valley theory (Mori et al., 2012), which suggests that the more nonhuman entities resemble humans, the more likeable they are. However, when this resemblance is taken too far, they are perceived as creepy and discomforting. Empirical findings align with this proposed effect (Castelo et al., 2019; K. Gray & Wegner, 2012; W. Kim et al., 2024; Mara et al., 2022; Mende et al., 2019). Moreover, it has been proposed that resemblance to humans evokes perceived capabilities to feel and sense and that this is the cause of the discomfort felt towards nonhuman entities (K. Gray & Wegner, 2012). Consequently, if an autonomous vehicle is designed with humanized features, it might be perceived as capable of feeling and sensing. In turn, this could increase perceived creepiness.

H1e*:* Technology humanization positively influences perceived creepiness

Consumers may be more willing to attribute nonhuman objects cognitive abilities rather than emotional abilities (Castelo et al., 2019). It has been suggested that humans believe that nonliving entities should not be capable of experiencing feelings or emotions (K. Gray & Wegner, 2012) since emotionality is perceived as distinctly human (Epley, 2018; Haslam, 2006; Waytz et al., 2014). In humanizing design, signs of emotionality are often emphasized, which could amplify the perceived creepiness. According to Mori et al. (2012), as objects are perceived as creepier, people feel less affinity for them. Drawing on this, it is proposed that the creepier the autonomous vehicle is, the less human it will be perceived.

H2e*:* Perceived creepiness negatively influences perceived humanness

2.2.6. Perceived humanness as a higher-order construct

The thesis adopts Söderlund & Oikarinen's (2021) concept of perceived humanness, defined as "the extent to which an individual has characteristics that are typical for humans". Perceived humanness refers to how similar a nonhuman entity is to other human beings in behavior and interaction (Söderlund et al., 2021). It is thus the most specific aspect of anthropomorphism. Söderlund et al. (2021) describes that when

nonhuman agents display humanlike traits it evokes a sense of similarity in the human that is interacting with the entity. Similarity triggers elicited agent knowledge that leads to nonhuman entities being perceived as more human. (Epley, 2018; Epley et al., 2007; section 2.1)

The current thesis adopts some of the human traits used by Söderlund & Oikarinen (2021), such as agency and morality, while including other traits deemed distinctly human. Perceived humanness is thus used as a higher-order construct (Söderlund & Oikarinen, 2021). All variables (competence, agency, warmth, morality, creepiness) represent distinct aspects of perceived humanness. As such, they collectively provide aspects of what it means for a nonhuman entity to be humanlike. Integrating multiple human traits into the theoretical framework allows for a detailed evaluation of which perceived human traits are the best for conveying humanness of nonhuman entities.

2.3. Anthropomorphism's potential outcomes

Anthropomorphizing nonhuman entities (Epley, 2018; Epley et al., 2007) could have multiple outcomes, such as increasing trust (de Visser et al., 2016; Feng et al., 2024; J.-C. Lee & Chen, 2022; van Pinxteren et al., 2019; Waytz et al., 2014), influencing perceived risks (Cui, 2022; Y. Hu & Min, 2023; S. Kim & McGill, 2011), positively influence behavioral intentions (Gursoy et al., 2019; Hsieh & Lee, 2024; Kelly et al., 2023; Lin et al., 2020; Pillai & Sivathanu, 2020; van Pinxteren et al., 2019) and affecting liking (S. Y. Kim et al., 2019; Stroessner & Benitez, 2019; Waytz et al., 2014). Further, it has also been shown that perceived humanness positively influences customer satisfaction (Söderlund & Oikarinen, 2021) and service quality (Söderlund, 2022). However, findings also indicate that there are negative outcomes of anthropomorphism (Castelo et al., 2019; Fernandes & Oliveira, 2021; Hadi, 2019; S. Kim & McGill, 2011; W. Kim et al., 2024; Lu et al., 2019; Mende et al., 2019; M. Wu, 2023) and that it might not yield any significant outcomes at all (Alain Goudey, 2016).

For autonomous technologies – vehicles in particular – trust, risks, and emotional valence can be seen vital outcomes and will therefore be the focus in this thesis. These outcomes will then be considered regarding their potential impact on product attitudes, which, informed by the theory of planned behavior (Ajzen, 1991), can be expected contribute to behavioral intentions driving potential behavior, as will be examined in the last section.

2.3.1. Trust

Trust is relevant in situations where one party depends on another party to perform tasks that inherently involve significant risks (Castelo et al., 2019). Trust is thus important in autonomous vehicle studies as it involves the risk of driving and the dependence on the vehicle to do so. Trust has also been applied widely in anthropomorphism studies (de

Visser et al., 2016, 2017; Fernandes & Oliveira, 2021; Glikson & Woolley, 2020; Hancock et al., 2011; Hsieh & Lee, 2024; Kelly et al., 2023; J.-C. Lee & Chen, 2022; J.-G. Lee et al., 2015; Pillai & Sivathanu, 2020; Schreiter et al., 2022; van Pinxteren et al., 2019; Verberne et al., 2015; Waytz et al., 2014). Interpersonal trust is used in this thesis, defined as "the extent to which a person is confident in, and willing to act on the basis of, the words, actions, and decisions of another" (McAllister, 1995). This form of trust is used because although people might be aware that an autonomous vehicle is programmed by a person, it is assumed that they evaluate trust in respect to the vehicle and not the programmer. This is because people can view anthropomorphic entities as distinct social beings (section 2.1).

Research show that anthropomorphism fosters trust in interactions with humanoid robots (Hancock et al., 2011; Schreiter et al., 2022; van Pinxteren et al., 2019), AI (Glikson & Woolley, 2020; J.-C. Lee & Chen, 2022), computers (de Visser et al., 2016) and autonomous vehicles (Waytz et al., 2014). Trust is closely related to perceived warmth, as in the SCM (see section 2.2.1 and 2.2.3). Warmth increases perceived humanness by enhancing ingroup and similarity perception (section 2.2.3). In turn, perceived humanness could positively influence perceived trust.

According to the consumer acceptance of technology model (CAT; Kulviwat et al., 2007), attitudes towards technology adoption are determined by cognitive evaluations (perceived usefulness, ease of use, and relative advantage) and affective feelings (arousal, pleasure and dominance). Furthermore, trust has also been divided into cognitive and affective dimensions (Castelo et al., 2019; Q. Chen et al., 2023; Q. Q. Chen & Park, 2021; Glikson & Woolley, 2020; Komiak & Benbasat, 2006a; McAllister, 1995; Wang et al., 2016). Drawing on this, it is proposed that trust influences product attitudes through the convergence of cognitive and affective factors. These aspects of trust and their proposed effects on product attitudes are explored further below.

Cognitive trust

Cognitive trust is about reliability (McAllister, 1995). It is based on circumstance and on what each person considers as logical and "good reasons" for trust, depending on personal dispositions and context (Lewis & Weigert, 1985). Cognitive trust is thus a factual measure of trust. For instance, Accuracy in AI recommendations can positively influence cognitive trust (Q. Chen et al., 2023)**.** Anthropomorphic nonhuman entities are likely to be attributed cognitive capabilities such as agency (H. Y. Kim & McGill, 2018; Müller et al., 2021; see section 2.2.2) and competence (see section 2.2.1). These traits suggest that the entity has the capability to perform tasks with intent and reliability. Consequently, cognitive trust should increase. Furthermore, competence and agency are positive accreditations, which suggest that attitudes towards nonhuman entities, such as autonomous vehicles, might also be positive.

H3a*:* Perceived humanness positively influences cognitive trust

Cognitive trust is driven by reliability and dependability (McAllister, 1995), and is formed by rational evaluations. Such cognitive, rational product evaluations are central in forming attitudes: According to the CAT model (Kulviwat et al., 2007), positive cognitive evaluations of technology evoke positive attitudes towards the technology. Drawing on this, it is proposed that the perception of cognitive trust, i.e., the perception of a reliable, dependable, and useful product, will lead to positive product beliefs. Consequently, it is proposed that cognitive trust positively influences product attitudes.

***H4a**:* Cognitive trust positively influences product attitudes

Affective trust

Affective trust concerns the perception of the trustee's level of concern and affect towards the trustor (McAllister, 1995). It is the perception that the one we trust cares about us. It is a representation of the emotional investments made when deciding to trust another (Lewis & Weigert, 1985). Moreover, affect describes perceived closeness, warmth and psychological attachment (Wang et al., 2016). Affective and cognitive trust can be seen as "opposite sides of the same coin". It's necessary to include this aspect of trust as people rely on emotional influences[1] in addition to cognitive evaluation when trusting others (Komiak & Benbasat, 2006b).

Interpersonal attraction theory (Byrne & Griffitt, 1973) describes people's motivations to form interpersonal relationships and consists of three dimensions: task, social and physical attraction (McCroskey & McCain, 1974), out of which social attraction is applicable to affective trust. It describes an entity's ability to foster positive emotional connections and relational bonds to others (McCroskey & McCain, 1974). This theory is considered applicable because people use social cognition to treat nonhuman entities as if they were social beings (section 2.1), perceiving them as someone to form emotional bonds with. The positive influence of anthropomorphism on social attraction and subsequent trust has been shown empirically (Q. Q. Chen & Park, 2021). Humanlike agents have also empirically been shown to have greater social presence, leading them to be perceived as more affectively trustworthy (J.-G. Lee et al., 2015). Consequently, perceived humanness through social features could influence affective trust.

***H3b**:* Perceived humanness positively influences affective trust

Affective trust is closely related to attitudes. In fact, emotional trust has been treated as equivalent to behavioral attitudes (Komiak & Benbasat, 2006a). Similarly, attitudes towards using a technology have been referred to as the overall affective reaction to using it (Venkatesh et al., 2003). Further, according to the CAT model (Kulviwat et al.,

[1]A clarification on emotional and affective trust is warranted as they are correlated and sometimes used interchangeably. Emotional trust refers to the "trustor's feeling toward the behavior of relying on the trustee, while the affect in affect-based trust refers to the trustee's affect toward the trustor" (Komiak & Benbasat, 2006a). Existing finding on emotional trust are assumed applicable to affective trust.

2007), the higher the level of affective feelings a consumer feels towards a technology, the more positive the attitude towards the technology. Drawing on this, it is proposed that affective trust evokes positive attitudes towards a product by fostering positive feelings, such as emotional security and closeness to the product. Consequently, it can be hypothesized that affective trust positively influences product attitudes due to their common emotional foundation.

***H4b**:* Affective trust positively influences product attitudes

2.3.2. Emotional valence

Emotional valence refers to emotions on a continuum ranging from pleasure to hostility (Liu et al., 2024), with positive emotional valence associated with pleasure. It is suggested that perceived positive emotions in nonhuman entities can "rub off" on people, who then experience positive emotions themselves (Liu et al., 2024). This is referred to as emotional contagion (Hatfield et al., 1993). The theory suggests that people adopt the emotions of those around them. It describes the tendency of people to mimic and synchronize expressions of others, leading to a convergence of emotions (Hatfield et al., 1993). Empathy towards the other party drives this process (Hatfield et al., 1993) and research shows that people can empathize with nonhuman beings, such as AI, when they exhibit humanlike traits (Liu et al., 2024). Based on theory and research, it is proposed that perceived humanness in autonomous vehicles, through displays of positive emotions, in turn induce positively valenced emotions in humans.

***H3c**:* Perceived humanness positively influences emotional valence

Furthermore, it is proposed that positive emotional contagion leads to positive product attitudes through affect infusion. Affect infusion is "the process whereby affectively loaded information exerts an influence on and becomes incorporated into the judgmental process" (Forgas, 1995). Simply put, when people are in a positive emotional state, they judge products more favorably by relying on their current state of mind. Consequently, it is likely that people, in a positively valenced state of mind, will evaluate products in more positive terms through affect infusion.

***H4c**:* Emotional valence positively influences product attitudes

2.3.3. Perceived risks

Perceived risks arise due to uncertainties about the use of autonomous vehicles (Ribeiro et al., 2022), and it involves concern about safety, vulnerability and risks in general. Perceived risk is essential in shaping behavior in situations where uncertainty and novelty are present (Ribeiro et al., 2022). Risks are important to consider as autonomous vehicles are associated with safety concerns (Othman, 2021). Surveys indicate that the majority of people asked are worried about the safety of using

autonomous vehicles (Rezaei & Caulfield, 2020; Schoettle & Sivak, 2014, 2015b). Anthropomorphism has been shown to influence risk perceptions, but effects are equivocal, and personal moderators appear to play a part (Cui, 2022; S. Kim & Mcgill, 2011). However, anthropomorphism is an attempt to interact more efficiently with one's environment, occurring because people want to reduce uncertainty and increase predictability (Epley et al., 2007). As mentioned, perceived risks arise because there is associated uncertainty with the nonhuman entity. Thus, it is hypothesized that increasing perceived humanness can reduce uncertainty and thereby reduce perceived risks with autonomous vehicles.

H3d: Perceived humanness negatively influences perceived risks

Perceived risks are fundamental to consumer behavior (Mitchell, 1992). Theory suggests that products with perceived risks are associated with uncertainty about whether purchases will result in positive or negative outcomes (Mitchell, 1992). In this context, essentially, people worry about whether they risk losing something by interacting with a nonhuman agent. Furthermore, according to prospect theory, people tend to be loss averse (Kahneman & Tversky, 1979; Levy, 1992). Drawing on these theories, it is proposed that people will avoid purchasing a product with high perceived risk to avoid potential losses. Negative views of a product will likely affect the associated product attitude negatively as well.

H4d: Perceived risks negatively influence product attitudes

2.3.4. Product attitudes and intentions to use

Attitudes are overall evaluations of objects or behaviors (Ajzen, 1991). Thus, positive product attitudes are positive evaluations of products. Product attitudes are common in marketing studies, given the notion that attitudes can influence consumer behavior (Argyriou & Melewar, 2011). This notion is considered in the framework of the Theory of Planned Behavior (TPB; Ajzen, 1991). The TPB posits that behavior is the result of behavioral intentions affected by behavioral attitudes, subjective norms and perceived behavioral control. From a marketing perspective, subjective norms and perceived behavioral control are more difficult to influence, which is why affecting attitudes is the primary focus. A primary antecedent of behavioral attitudes is beliefs. Consequently, positive product beliefs can lead to positive product attitudes, contributing to subsequent behavioral attitudes, intentions and, potentially, finally behavior. While the TPB emphasizes behavioral attitudes, marketing applications often focus on product attitudes as they can be assumed to affect behavioral attitudes and subsequent consumer intentions, which ultimately might influence purchase behavior. Thus, our final hypothesis becomes:

H5: Product attitudes positively influence intentions to use

An intention is a mental state, indicating effort to pursue a course of action (Ajzen, 1991). However, in marketing, "intentions" are used more loosely than in psychology and could rather be referred to as behavioral expectations, estimating the likelihood of behavior (Sheeran, 2002). Furthermore, intentions do not guarantee behavior (Conner & Norman, 2022; Feil et al., 2023). Nevertheless, intentions to use is a common dependent variable in many anthropomorphism and technology adoption studies (Alain Goudey, 2016; Blut et al., 2021; Cao et al., 2021; Kelly et al., 2023; Pillai & Sivathanu, 2020; van Pinxteren et al., 2019; Venkatesh et al., 2003; Venkatesh & Davis, 2000). Therefore, intentions to use, as conceptualized in marketing, was incorporated in this study to ensure compatibility with use in studies on anthropomorphism and technology adoption. Conclusively, intentions to use should not be interpreted from a psychological perspective, but rather as it is commonly applied in marketing.

2.4. Summary and visualization of hypotheses

Figure 1 represents the theoretical model with all hypotheses. A table summarizing the hypotheses is available in Appendix A.

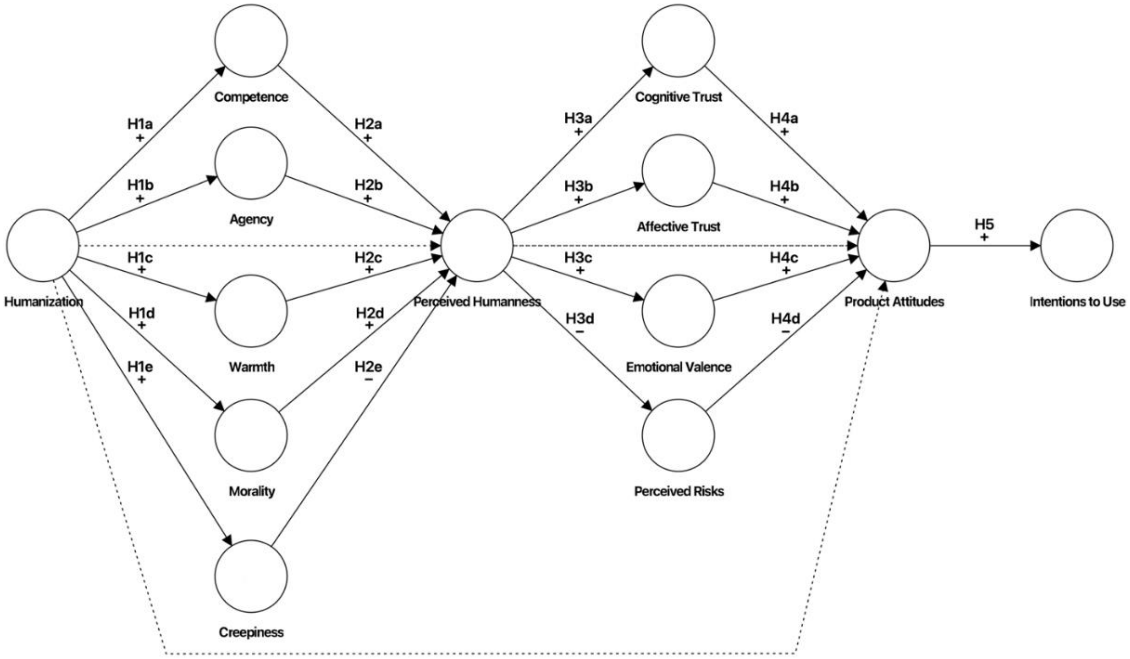


Figure 1. Summary and visualization of the study's hypotheses

Note: The dashed lines represent non-hypothesized direct effects that will be used for mediation testing.

3. Methodology

The methodology section explains the scientific approach of this study and provides a detailed account of the experiment design, including experimental stimuli development, data collection and filtering, study variables and measurements, applied data analysis techniques, and assessments of reliability, validity, and data quality.

3.1. Scientific approach

The scientific approach of this study is grounded in an objectivist ontology that posits that reality can be examined objectively as it exists independently of observers (Bell et al., 2022). This ontology informs the study's positivist epistemological position where, given that reality is external, data should be gathered through direct observations or measurements and analyzed according to a deductive logic of systematic hypothesis testing, building on existing science (Bell et al., 2022).

This study has two primary objectives. First, it aims to examine if, and how, human-like technology design (i.e., humanization) contributes to consumers' perceptions of technology humanness (i.e., anthropomorphism). Second, it seeks to assess whether, and through which mechanisms, anthropomorphism influences consumers' product attitudes and subsequent behavioral intentions relevant to marketers. Given that this study is conducted from a marketing perspective, the goal is to generate insights into effects and mechanisms on a general human level, independent of personal determinants or individual differences. To achieve this, a between-subjects experimental study was conducted to produce objective quantitative data for statistical testing of hypotheses constructed upon existing theories and empirical research (following the recommendations of Bell et al., 2022), aiming to provide insights that are broadly applicable to similar situations across the value chain of autonomous technologies.

Alternative methods considered include explorative qualitative research and quantitative behavioral research. First, while qualitative research can result in in-depth understandings of phenomena and the formulation of new theories through inductive, interpretive, and abductive logic (Bell et al., 2022), in this case, much indicates that individual differences and social norms have a significant effect on the tendency to anthropomorphize technology (Epley et al., 2007; Epley, 2018; Blut et al., 2021; Gursoy et al., 2019; Ribeiro et al., 2022; Hende & Mugge, 2014; Wirtz et al., 2018). Consequently, qualitative studies aiming for generalizable results regarding the effects of human-like technology design and anthropomorphism would need a vast number of participants to ensure that individual differences are equalized, which would not have been possible within this study's scope.

Second, a quantitative study based on behavioral or physical measurements from a simulation (e.g., Waytz et al., 2014) or an actual driving/riding situation could have enhanced the situation's realism and potentially increased the results validity. As such approaches are beyond the resources of this study – and self-reporting measures are commonly used within psychology and consumer research – the decision to conduct a quantitative experiment with self-reported measurements in correspondence to stimuli consisting of text-based scenarios (following Atzmüller & Steiner, 2010; and Aguinis & Bradley, 2014) is motivated given this study's goals and constraints.

3.2. Experiment design

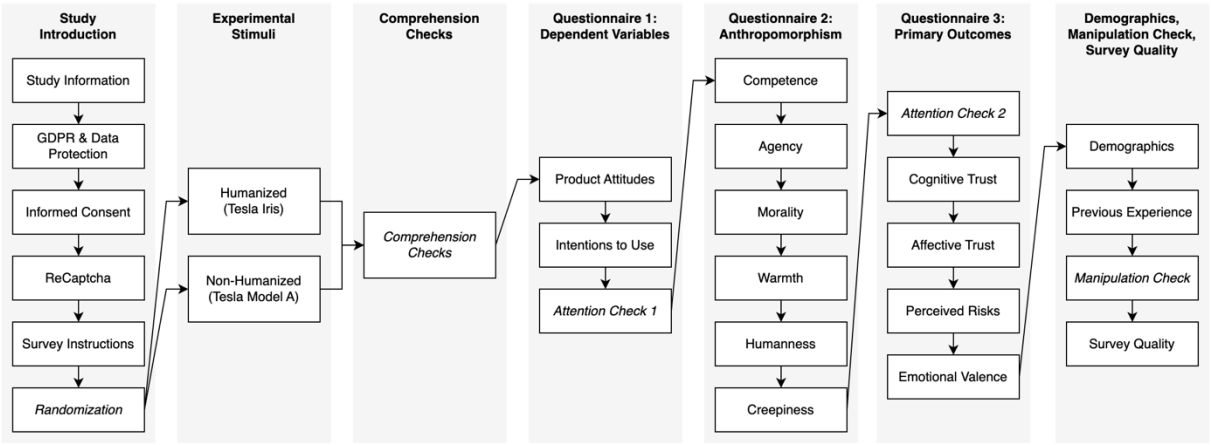


Figure 2. Overview of experiment design

The experiment was designed as a quantitative, scenario-based, between-subjects experiment, commonly known as a quantitative vignette study as it consisted of text-based scenario stimuli where specific factors vary, followed by a traditional survey (Atzmüller & Steiner, 2010). Concretely, a survey was constructed in Qualtrics and all participants who gave informed consent after reviewing the study introduction (see Appendix B) consisting of study information, instructions, GDPR/Data Protection, and ReCaptcha checks, were randomly assigned to one of two experimental text-based stimuli where they were asked to imagine themselves watching a commercial about a self-driving car. The stimuli varied between a very high degree of humanization (Tesla Iris) and no humanization (Tesla Model A), which are explained further in section 3.3. Participants who passed the stimuli comprehension checks then responded to the same questionnaire which included items representing multiple variables, attention- and manipulation checks. An overview of the experiment design is presented in Figure 2. The independent variable is consequently the humanization of the experimental stimuli (Tesla Iris vs. Tesla Model A), with the dependent variables being Product Attitudes and the subsequent Intentions to Use. As structural equation modelling was used for data analysis, all other variables simultaneously function as both independent and dependent variables, enabling full model mediation analysis (see section 3.6).

3.3. Experimental stimuli

Employing text-based scenarios – a.k.a. vignettes – as experimental stimuli can provide survey respondents with the ability to reason about their replies in a realistic context (Finch, 1987). A vignette is a "short, carefully constructed description of a person, object, or situation, representing a systematic combination of characteristics" (Atzmüller & Steiner, 2010), useful to present realistic scenarios which enhances experimental realism and allows researchers to systematically manipulate critical, independent variables in a controlled setting (Aguinis & Bradley, 2014). Within marketing, such scenario-based experiments have been used frequently within service- and human-robot interaction research (Söderlund, 2024a). A vignette approach was deemed suitable for the experimental stimuli as it could provide the participants with the most realism and relatability in the survey situation, given the study's resources, while allowing effective manipulation of the independent variables. Alternative approaches, such as displaying an altered or custom-made commercial to participants, were considered. However, such approaches offered no clear advantages and risked reducing study realism as it would be unfeasible to achieve a production quality comparable to existing auto commercials.

Consequently, a text-based scenario was created where participants were asked to imagine watching a commercial about a self-driving car. The scenario was designed to convey a vibrant, engaging, and realistic story that encouraged participants to think about aspects of human-autonomous vehicle interactions, including the AV's capabilities, autonomy, safety, and risks, as well as passenger convenience, experience, and enjoyment. It was framed as a commercial, instead of asking participants to imagine themselves as passengers, as fully self-driving cars are not yet widely available[2]. An AV commercial was thus assumed to be closer to participants' reality, while also being relevant from a marketing perspective as increasing adoption of autonomous technology will likely be a core objective for marketers over the foreseeable future.

The scenario was then used to create two experimental stimuli by varying the degree of human-like technology design, as described below, while keeping the depicted situation constant. This resulted in one highly humanized stimulus, Tesla Iris, and one non-humanized stimulus, Tesla Model A, both which can be read in full in Appendix C. Tesla was named as manufacturer as it is the most preferred brand for self-driving cars (Eggers & Eggers, 2022) and thus more likely to be perceived as realistic. To enable fair comparisons and further increase study realism as AI interactions are now common, both cars were described as AI-powered, aiming to present participants with relatable entities in terms of each car's respective "driver" (i.e., Model A's AI vs. Iris).

[2] In the U.K., where this study was conducted, self-driving vehicles are expected to be on roads by 2026 (Gov.uk, 2024).

3.3.1. Humanized stimulus: Tesla Iris

Drawing on existing research on human-like technology design (see section 2.3) the humanized stimulus, Tesla Iris (see Appendix C), aimed to imbue the car with as many humanizing design factors as possible while maintaining scenario realism. The car was given the *human name* Iris[3] which contributed to *gender cues*, reinforced by its voice and the stimulus language, suggesting that the car was female. It was given a *voice* (e.g., "a female voice in the speakers that says...") in contrast to Model A that only communicates by text on the dashboard display. Its *facial features* and *gaze* ("a display shows a face that begins to smile when making eye-contact") potentially increased the realism of its social interactions and allowed it to display *mimicry* by reacting to situations with facial expressions ("Iris' face looks concerned", "Iris' expression turns happy and calm"). Furthermore, the car was *referred to as a person* in both the commercial and scenario text ("Iris is your personal driver", "Iris navigates rush hour traffic", "Iris says"), making the stimulus language itself a humanizing factor.

These human-like design features allowed Tesla Iris to communicate with the passenger in several ways. The car could express *emotions* such as happiness ("I'm so happy to be driving you!") and excitement ("Fun!"). This ability to simulate emotions allowed the car to demonstrate aspects of *warmth*, including friendliness and sociability ("...are you excited about going downtown together?"), empathy ("I'm sorry you're feeling tired"), caring ("Don't worry! I'm keeping all of us safe"), as well as humor ("Wow, that was clearly not an AI powered car!"). Additionally, it could convey aspects of *competence* such as problem-solving ("I can get us [there] faster") and perception ("I heard that there will be more traffic than expected"), a sense of *agency* ("I've been looking forward to it", "Let's take the better route"), as well as *morality* ("I'm just happy that no one got hurt"). Consequently, the car was endowed with multiple human-like abilities and traits relevant for testing the study's hypotheses based on the presented theories.

3.3.2. Non-humanized stimulus: Tesla Model A

The non-humanized stimulus, Tesla Model A (see Appendix C), was constructed to be an inverse of Tesla Iris in terms of humanization[4]. Model A thus neither had a human name, a voice, a gender, facial features, gaze, nor mimicry. All interaction was done through the dashboard display where Model A displayed neutral prompts and status messages (e.g., "Select destination", "Replanning route", "Collision avoided") and the passenger input was limited to tapping on the display. Accordingly, Model A did not

[3] The name Iris was chosen as an homage to Waytz et al.'s (2014) influential autonomous vehicle experiment and their clever inverse of Siri, the well-known name of Apple's voice assistant since 2011.
[4] Model A was further inspired by Tesla's recent robotaxi prototype where user interactions are even fewer than in existing Tesla AVs: passengers are limited to selecting their destination and deciding what entertainment to stream during their ride (Auto Focus, 2024). This suggests that Tesla is moving toward a non-humanized approach, potentially aiming to distract passengers with entertainment rather than engaging them with interaction.

have Tesla Iris' ability to simulate human communication and emotions, nor convey human-like traits like morality. It was consistently referred to as a non-human entity ("Model A is the car that...", "The car's AI navigates rush hour traffic", "The car's display reads") with the distinction that the "Car's AI" was described as controlling the vehicle. This approach was intended to enable fair comparisons and ensure that survey questions would be perceived as realistic by respondents exposed to either stimulus.

3.4. Data collection

Data was collected online using a Qualtrics survey distributed through the Prolific platform, which connects researchers with study participants and has been shown to generate higher data quality in participant attention, comprehension, honesty, and reliability compared to competitors (Peer et al., 2022). A total of 210 participants, equally split between male and female UK residents fluent in English, were recruited between November 1–8, 2024.

3.4.1. Data filtering and sample demographics

Participants who gave informed consent were randomly exposed to one experimental stimulus followed by three comprehension checks to ensure that they had fully read and understood the scenario. Ten participants were excluded for either failing these checks or denying participation according to the study information/GDPR. An additional eight participants were removed for failing at least one of two attention checks (see Appendix D for details on comprehension- and attention checks). Participants with response times one standard deviation below the mean survey time (M = 11.98, SD = 6.53) or with straightlining above 85% were manually reviewed, and four were further removed. The remaining sample consisted of 189 respondents, 51% females and 49% males, with an average age of 39 years (SD = 14). 86% had a driver's license, 13% had experience of riding in an autonomous vehicle, and 5% had experience of driving an AV themselves. Demographic data was used to verify that the Qualtrics randomization worked as intended and did not result in any notable differences in gender, age, or experience across the study groups. Sample demographics can be reviewed in Appendix E.

3.5. Variables and measurements

After being exposed to the experimental stimuli, participants completed a questionnaire that included multi-item measures of the study's variables (see Appendix F). Most items were measured on a 7-point Likert scale ranging from (1) strongly disagree to (7) strongly agree, while product attitudes and emotional valence were assessed using 7-point semantic differential scales with bipolar adjectives. A majority of the measures were based on established theories or existing research, as explained further below.

Anthropomorphism has often been measured by combining several human-like items, such as intelligence, agency, or emotionality, into one aggregated measure (e.g., Gursoy et al., 2019; Waytz et al., 2014). This has resulted in multiple measures of anthropomorphism, and such inconsistencies can prevent meaningful comparisons in human-robot interaction (HRI) research (Bartneck et al., 2009). This study therefore aims for a detailed approach to measuring anthropomorphism (see Section 2.2) to facilitate future comparisons. It adopts Söderlund & Oikarinen's (2021) measure of *perceived humanness* as a specific indicator of the extent to which technology is perceived as human (i.e., anthropomorphized). It further incorporates their measures of human-like traits that are potential antecedents to perceived humanness: *perceived agency*, and *perceived morality*. These antecedents are complemented by measures of *perceived competence* commonly used in HRI-research, adapted from the Godspeed human-robot interactions scale (Bartneck et al., 2009) and the Robot Social Attributes Scale (Carpinella et al., 2017), as well as *perceived warmth* adapted from Hu (2021) and Hsieh & Lee (2024). Additionally, *perceived creepiness* was adopted from Söderlund (2022), and is similar to the discomfort measure developed by Castelo et al. (2019).

The measures for anthropomorphism's potential outcomes were similarly selected to align with established theories and studies wherever possible, ensuring their relevance for future research. Cognitive trust was constructed based on items from the Artificially Intelligent Device Use Acceptance Model (AIDUA; Gursoy et al., 2019), the Autonomous Vehicle Acceptance Model (AVAM; Ribeiro et al., 2022), and Castelo et al. (2019). Affective trust items were developed to correspond to the definition by McAllister (1995) as described in section 2.3.1. Perceived risks were adopted from the AVAM-model (Ribeiro et al., 2022). Emotional valence and product attitudes were measured using scales that are widely accepted in psychology and marketing research (Söderlund, 2024b). The items in intentions to use were adapted from measurements commonly used regarding technology adoption (Venkatesh & Davis, 2000; Gursoy et al., 2019; Ng et al., 2020; Ribeiro et al., 2022). See Table 1 for an overview of the study variables, number of items, reliability and validity indicators, and measurement sources. More details, including survey items and factor loadings, are available in Appendix F.

Table 1. Study variables, number of items, reliability and validity indicators, and sources used for measures

Variable	Items	CA	CR	AVE	Sources of measures
Perceived competence	3	0.93	0.95	0.87	Bartneck et al. (2009), Carpinella et al. (2017)
Perceived agency	4	0.80	0.87	0.63	Söderlund & Oikarinen (2021)
Perceived warmth	5	0.96	0.97	0.86	Hu (2021), Hsieh & Lee (2024)
Perceived morality	3	0.92	0.95	0.86	Söderlund & Oikarinen (2021)
Perceived creepiness	3	0.89	0.93	0.81	Söderlund (2022), Castelo et al. (2019)
Perceived humanness	3	0.95	0.97	0.92	Söderlund & Oikarinen (2021)

Cognitive trust	6	0.94	0.95	0.77	Gursoy et al. (2019), Ribeiro et al. (2022), Castelo et al. (2019)
Affective trust	3	0.94	0.96	0.89	Based on McAllister (1995)
Emotional valence	3	0.92	0.95	0.87	Established measure (Söderlund, 2024b).
Perceived risks	3	0.93	0.96	0.88	Ribeiro et al. (2022)
Product attitudes	3	0.97	0.98	0.93	Established measure (Söderlund, 2024b).
Intentions to use	3	0.98	0.99	0.96	Venkatesh & Davis (2000), Gursoy et al. (2019), Ng et al. (2020), Ribeiro et al. (2022)

Note: See Appendix F for details including measure items (i.e., survey questions) and factor loadings.

3.6. Data analysis techniques

Survey responses were collected in Qualtrics. Microsoft Excel was used for data filtering and demographics analysis (see section 3.4.1) while IBM SPSS Statistics was used for descriptive statistics and an independent samples t-test (see section 4.1). The data was assumed to be normally distributed as each group contained over 30 participants (Kwak & Kim, 2017). The data was then imported into SmartPLS 4.1 for analysis using partial least squares structural equation modelling (PLS-SEM).

PLS-SEM was chosen as the primary data analysis technique as it is considered particularly useful for estimating complex models with numerous constructs, indicators, and structural paths, providing high statistical power even with small sample sizes, while being widely accepted within social sciences (Hair et al., 2019). The method enables the simultaneous modelling of complex relationships between multiple independent and dependent variables. In practice, model relationships are analyzed sequentially with intermediate variables functioning as both dependent and independent variables as the model maximizes the overall explained variance (Hair et al., 2022). Consequently, PLS-SEM can simultaneously estimate direct, indirect, and total effects in multiple-mediation models. It is argued to be the superior mediation estimation approach as it considers the entire model while accounting for measurement errors (Sarstedt et al., 2020). Furthermore, given that PLS-SEM allows for detailed evaluation of the measurement model's reliability and validity, and of the structural model's path coefficients, significance, explanatory power, and mediation, it is highly suitable for studies based on multi-item measurements, such as this one.

Following the PLS-SEM evaluation guidelines by Hair et al. (2022), the study model was first assessed as a reflective measurement model by considering indicator and internal consistency reliability and convergent and discriminant validity, as described in section 3.7. Multicollinearity was assessed using VIF values, which were predominantly below the stricter threshold of 3.0, except for one instance which was below the acceptable threshold of 5.0 (Hair et al., 2022; see Appendix G). The study's structural model was then tested for statistical significance by performing bootstrapping with

10 000 subsamples using a two-tailed test with a 5% significance level and the percentile bootstrap confidence interval method. The magnitudes, signs, and significances of the model's path coefficients and the model's explanatory power examined according to the coefficients of determination (i.e., R^2 values) are all assessed in section 4.2. Predictive relevance or model fit were not assessed as these methods are subject to much debate (Hair et al., 2022) and they were not considered appropriate for this study. Mediation analysis was done fully within PLS-SEM using bootstrapped confidence intervals, as this has been argued to be the preferred approach for estimating complex mediation models (Sarstedt et al., 2020), with results in section 4.3.

3.7. Reliability, validity, and data quality

Responses were assessed for reliability, validity, and data quality before being used to test the study hypotheses. Table 1 provides an overview of the study's variables, the number of items used to measure each variable, and key reliability and validity indicators, which are evaluated in this section. A detailed account, including all study items and factor loadings, is available in Appendix F.

3.7.1. Reliability

Reliability refers to the extent to which several measurements of constructs provide similar results, and it is commonly assessed by using multiple observations (Söderlund, 2018). To reliably measure self-reported psychological reactions, this study adopts the standard approach of using multiple questions to measure each variable and evaluating responses using established methods for estimating reliability (Söderlund, 2018).

Indicator reliability examines how consistently items reflect the variation of the construct they are intended to measure in PLS-SEM reflective measurement models. Indicator reliability was confirmed as all factor loadings exceeded 0.708 (J. Hair et al., 2022), ranging between 0.73 and 0.98 for the study items (see Appendix F). *Internal consistency reliability* is a common reliability assessment which tests the consistency among items used in multi-item construct measures. Internal consistency reliability was established as Cronbach's Alpha (CA) and composite reliability (CR) were both greater than 0.7 (J. Hair et al., 2022), with CA ranging from 0.80 to 0.98 and CR ranging from 0.87 to 0.99 for the study's variables (see Table 1 or Appendix F). Reliability can also be assessed through *stability over time* (e.g., by test-retest methods) or *inter-rater reliability* if researchers' subjective judgements influence study results (Bell et al., 2022). While stability over time was not within the study's scope, responses are assumed to remain stable over shorter periods of time, given the study's subject. Inter-rater reliability was not applicable as subjective judgement did not influence data collection or interpretation. In summary, both indicator and internal consistency reliability was confirmed in support of the reliability of the study measures.

3.7.2. Validity

Validity concerns the degree to which a measurement truly measures what it is intended to measure (Söderlund, 2018). It presumes reliability as measures that are not reliable cannot be valid (Bell et al., 2022). Given that all of the study's measures were found reliable in the previous section, they were then examined for validity.

Content validity refers to whether the items used to measure a construct represent the full extent of this construct according to the theory upon which it is based (Söderlund, 2018). This was ensured as the study's questions were based on its theoretical framework and answered on scales capturing extreme values, such as 7-point Likert scales or semantical differential scales (see section 3.5: Variables and measurements). *Construct validity* assesses whether measurements accurately measure their theoretical constructs (Söderlund, 2024c, p. 4). First, this was enhanced by basing the majority of the study items on measures validated by previous research (Bell et al., 2022). Second, it was tested by evaluating the study's structural equation model in terms of convergent and discriminant validity. *Convergent validity*, which analyzes the positive correlation between one measure and alternative measures of the same construct, was confirmed as the average variance extracted (AVE) surpassed the threshold of 0.50 for all study constructs, with values spanning 0.63 to 0.96 (see Table 1 or Appendix F). *Discriminant validity*, which examines if a construct is unique and distinct from other model constructs, was established as the heterotrait-monotrait ratio (HTMT) values were all below 0.85 and their bias-corrected confidence intervals did not exceed 0.90[5] (Henseler et al., 2015). Content validity and construct validity, including convergent and discriminant validity, were thus established, demonstrating that the study's measures accurately captured their intended constructs.

3.7.3. Data quality

Data quality was ensured by removing respondents who failed attention checks, comprehension checks, had very fast response times, or exhibited straightlining (Jones et al., 2015), as described in section 3.4.1. Furthermore, since perceived realism is an important factor for scenario-based experiments (Söderlund, 2018) and clear, non-leading questions contribute to data quality (Bell et al., 2022), respondents were asked to evaluate the survey on these aspects (see Appendix H). A majority of the participants found the presented scenario realistic (M = 5.69, SD = 1.18), the survey questions clearly formulated (M = 6.20, SD = 0.77), that the survey did not try to influence their answers (M = 6.06, SD = 0.98), and that the survey was meaningful (M = 5.74, SD = 1.10). These results suggest that participants were motivated and able to provide high-quality responses, and thus further enhances the credibility of the study's findings.

[5] The heterotrait-monotrait ratio test results were too long to report in the appendix but are available from the authors upon request.

4. Results

This section presents the experiment results analyzed using the techniques described in section 3.6. Descriptive statistics and findings from an independent samples t-test are reported as an overview of the experiment's outcomes. Hypotheses are then tested in the order they were introduced in the theory section. Finally, an explorative analysis of significant mediation effects offers insight on the impacts of humanization and perceived humanness within the full study model.

4.1. Sample, descriptive statistics, and t-test results

The final sample consisted of 189 participants after the filtering process (see section 3.4.1). All were UK residents with an average age of 39 years (*SD* = 14). 51% of the participants were female, and 49% were male. 86% held a driver's license, 13% had experience of riding in an autonomous vehicle, and 5% had driven an AV themselves. The randomization process successfully prevented significant differences between study groups in terms of age, gender, or experience. Detailed demographics are provided in Appendix E. Table 2 presents descriptive statistics for the study variables, along with the results of an independent samples t-tests conducted to compare the experimental groups. The significant results of the manipulation check and perceived humanness confirmed that the experimental manipulation had functioned as intended. For reference, a correlation matrix of the study variables is available in Appendix I.

Table 2. Descriptive statistics and independent samples t-test results

Experimental group	Non-humanized stimulus *n* = 96		Humanized stimulus *n* = 93		Difference	Independent samples t-test	
Variable	*M*	*SD*	*M*	*SD*	*M* diff.	*t*	*p*
Competence	5.71	0.94	5.68	1.14	0.03	0.18	.858
Agency	4.82	1.18	5.16	0.98	-0.35	-2.20	< .05*
Morality	4.19	1.57	4.97	1.34	-0.78	-3.67	< .001***
Warmth	4.02	1.40	5.26	1.32	-1.25	-6.30	< .001***
Creepiness	3.51	1.52	3.70	1.57	-0.19	-0.84	.402
Perc. Humanness	3.64	1.53	4.38	1.41	-0.74	-3.48	< .001***
Cognitive Trust	5.03	1.21	5.16	1.32	-0.13	-0.69	.494
Affective Trust	4.03	1.57	4.20	1.61	-0.18	-0.76	.445
Emotional Valence	4.59	1.41	4.65	1.45	-0.06	-0.28	.779
Perceived Risks	4.66	1.39	4.36	1.65	0.30	1.34	.181
Product Attitude	5.26	1.62	5.20	1.68	0.06	0.23	.816
Intentions to Use	4.76	1.84	4.90	1.88	-0.14	-0.50	.616
Manipulation Check	3.46	1.24	5.71	1.18	-2.25	-12.76	< .001***

Note: $n = 189$, $df = 187$, two-tailed test. *p < .05, **p < .01, ***p < .001.

4.2. Hypothesis testing

The hypotheses were tested using partial least squares structural equation modelling (PLS-SEM) as described in section 3.6. Figure 3 visually summarizes the model results, including path coefficients, p-values, and R^2 values, with a full-page version in Appendix J. Table 3 adds detail by describing the study's hypothesized paths along with t-values, while Table 4 organizes the R^2 values of the models' dependent variables. Non-hypothesized paths were included to enable explorative mediation analysis in section 4.3. Hypotheses test results are summarized in Appendix K.

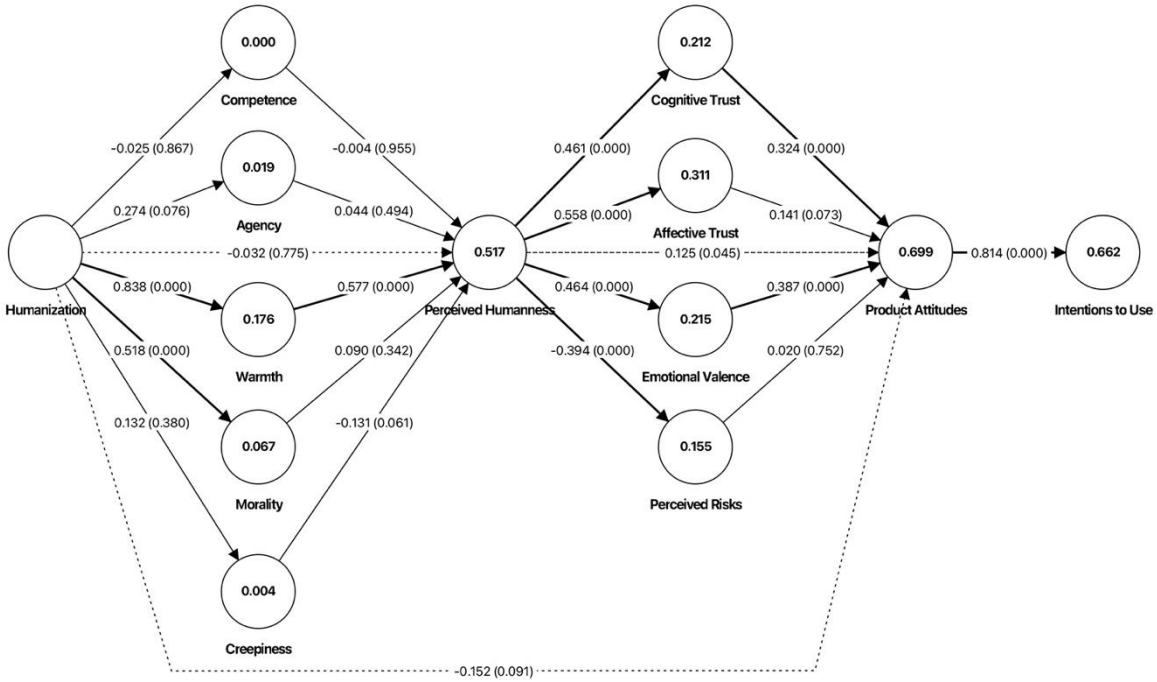


Figure 3. PLS-SEM results for the hypothesized model

Note: The figure presents path coefficients (β) with p-values in parenthesis on the connections, and R^2 values inside the constructs. Bold lines denote significant paths. Solid lines represent hypothesized paths, while dashed lines represent non-hypothesized paths.

Table 3. Hypothesized paths and PLS-SEM results

Hypothesized path		Path coefficient (β)	*t*	*p*	
H1a	Humanization → Competence	-0,025	0.17	0.867	n.s.
H1b	Humanization → Agency	0.274	1.78	0.076	n.s.
H1c	Humanization → Warmth	0.838	6.76	< 0.001	***
H1d	Humanization → Morality	0.518	3.78	< 0.001	***
H1e	Humanization → Creepiness	0.132	0.88	0.380	n.s.
n.h.	Humanization → Perceived Humanness	-0.032	0.29	0.775	n.s.
H2a	Competence → Perceived Humanness	-0.004	0.06	0.955	n.s.
H2b	Agency → Perceived Humanness	0.044	0.68	0.494	n.s.

H2c	Warmth → Perceived Humanness	0.577	7.01	< 0.001	***
H2d	Morality → Perceived Humanness	0.090	0.95	0.342	n.s.
H2e	Creepiness → Perceived Humanness	-0.131	1.87	0.061	n.s.
H3a	Perceived Humanness → Cognitive Trust	0.461	6.98	< 0.001	***
H3b	Perceived Humanness → Affective Trust	0.558	10.33	< 0.001	***
H3c	Perceived Humanness → Emotional Valence	0.464	7.52	< 0.001	***
H3d	Perceived Humanness → Perceived Risks	-0.394	6.21	< 0.001	***
H4a	Cognitive Trust → Product Attitudes	0.324	4.04	< 0.001	***
H4b	Affective Trust → Product Attitudes	0.141	1.79	0.073	n.s.
H4c	Emotional Valence → Product Attitudes	0.387	5.08	< 0.001	***
H4d	Perceived Risks → Product Attitudes	0.020	0.32	0.752	n.s.
n.h.	Perceived Humanness → Product Attitudes	0.125	2.01	< 0.05	*
n.h.	Humanization → Product Attitudes	-0.152	1.69	0.091	n.s.
H5	Product Attitudes → Intentions to Use	0.814	26.14	0.000	***

Note: n.h. denotes non-hypothesized paths, while n.s. represents non-significance.

Table 4. R^2 values for dependent variables in the PLS-SEM model

Dependent variable	R^2	Dependent variable	R^2
Competence	0.000	Cognitive Trust	0.212
Agency	0.019	Affective Trust	0.311
Warmth	0.176	Emotional Valence	0.215
Morality	0.067	Perceived Risks	0.155
Creepiness	0.004	Product Attitudes	0.699
Perceived Humanness	0.517	Intentions to Use	0.662

4.2.1. H1: Technology humanization's effects on potential antecedents and impediments to perceived humanness

The first tests concerned the hypothesized direct effects of technology humanization. A strong, positive and significant relationship was found between Humanization and Warmth (H1c: $\beta = 0.838$, $t = 6.76$, $p < 0.001$) and H1c was supported. However, the R^2 value for Warmth ($R^2 = 0.176$) indicated that Humanization only explained 18% of the variation in participants' perception of Warmth, limiting practical implications. A positive, significant association was also found between Humanization and Morality (H1d: $\beta = 0.518$, $t = 3.78$, $p < 0.001$), but the low R^2 value ($R^2 = 0.067$) of Morality suggests that Humanization only explains 6.7% of its variance, and thus, we consider this as weak support for H1d. The relationships between Humanization and Competence (H1a: $\beta = -0.025$, $t = 0.17$, $p = 0.867$), Agency (H1b: $\beta = 0.274$, $t = 1.78$, $p = 0.076$), and Creepiness (H1e: $\beta = 0.132$, $t = 0.88$, $p = 0.380$) were not significant, leading to the rejection of H1a, H1b, and H1e. Additionally, the non-hypothesized direct relationship

between Humanization and Perceived Humanness was not significant (β = -0.032, t = 0.29, p = 0.775).

4.2.2. H2: Effects of antecedents to perceived humanness

Second, these antecedents and impediments were tested for their effects on Perceived Humanness. A positive, significant association was found between Warmth and Perceived Humanness (H2c: β = 0.577, t = 7.01, p < 0.001), supporting H2c. There were no significant effects on Perceived Humanness stemming from Competence (H2a: β = -0.004, t = 0.06, p = 0.955), Agency (H2b: β = 0.044, t = 0.68, p = 0.494), Morality (H2d: β = 0.090, t = 0.95, p = 0.342), or Creepiness (H2e: β = -0.131, t = 1.87, p = 0.061). H2a, H2b, H2d, and H2e were thus not supported. Combined, these effects accounted for approximately 52% of the variance in Perceived Humanness (R^2 = 0.517) when considered as a dependent variable.

4.2.3. H3: Perceived humanness' outcomes on affective and cognitive trust, emotional valence, and perceived risks

Third, significant associations were found between Perceived Humanness and Cognitive Trust (H3a: β = 0.461, t = 6.98, p < 0.001; R^2 = 0.212), Affective Trust (H3b: β = 0.558, t = 10.33, p < 0.001; R^2 = 0.311), Emotional Valence (H3c: β = 0.464, t = 7.52, p < 0.001; R^2 = 0.215), and Perceived Risks (H3d: β = -0.394, t = 6.21, p < 0.001; R^2 = 0.155). H3a, H3b, H3c, and H3d were therefore supported. Perceived Humanness explained approximately 16–31% of the variance of these constructs (see Table 4).

4.2.4. H4–H5: Downstream effects on product attitudes and intentions

Fourth, Product Attitudes was found to be positively affected by Cognitive Trust (H4a: β = 0.324, t = 4.04, p < 0.001) and Emotional Valence (H4c: β = 0.387 t = 5.08, p < 0.001), supporting H4a and H4c. Affective Trust (H4b: β = 0.141, t = 1.79, p = 0.073) and Perceived Risks (H4d: β = 0.020, t = 0.32, p = 0.752) did not have significant effects on Product Attitudes, and H4b and H4d were not supported. Considering non-hypothesized direct associations: Perceived Humanness–Product Attitudes was significant with a small coefficient (β = 0.125 t = 2.01, p < 0.05), while Humanization–Product Attitudes was not significant (β = -0.152 t = 1.69, p = 0.091). Combined, these variables explained approximately 70% of the variance in Product Attitudes (R^2 = 0.699). Finally, as expected, Product Attitudes had a strong, positive effect on Intentions to Use (H5: β = 0.814 t = 26.14, p < 0.001; R^2 = 0.662), supporting H5.

4.3. Explorative analysis of significant non-hypothesized mediation

It would have been unfeasible to hypothesize all potential mediation paths given the complexity of the study model and the lack of theory regarding all downstream effects of humanization and anthropomorphism. Instead, after testing for all direct effects between the variables, the specific indirect effects that were significant and relevant for the study's research questions were analyzed for mediation. Non-significant indirect effects were excluded from additional analysis. An overview of the selected significant indirect effects is presented in Table 5, while the full PLS-SEM output used for the mediation testing is available in Appendix L.

Table 5. Specific indirect effects tested for mediation

Specific Indirect Effects	*β*	*t*	*p*	
Humanization → Warmth → Perceived Humanness	0.483	4.63	< 0.001	***
Perceived Humanness → Emotional Valence → Product Attitudes	0.180	4.22	< 0.001	***
Perceived Humanness → Cognitive Trust → Product Attitudes	0.149	3.24	< 0.001	***
Humanization → Warmth → Perceived Humanness → Cognitive Trust → Product Attitudes	0.072	2.69	< 0.01	**
Humanization → Warmth → Perceived Humanness → Emotional Valence → Product Attitudes	0.087	2.87	< 0.01	**

The first step explored possible mediators between Humanization and Perceived Humanness. Warmth was analyzed as a potential mediator as it was the only variable with significant paths between the two constructs. The specific indirect effect (β = 0.483, t = 4.63, p = < 0.001, CI [0.295, 0.703]) was significant, while the direct effect (β = -0.032, t = 0.29, p = 0.775, CI [-0.254, 0.187]) was non-significant, indicating full mediation. The significant total effects (β = 0.492, t = 3.52, p = < 0.001, CI [0.204, 0.754]) confirmed Warmth's full mediation of the positive relationship between Humanization and Perceived Humanness.

The second step concerned potential mediators between Perceived Humanness and Product Attitudes. The significant total effect (β = 0.525, t = 8.07, p < 0.001, CI [0.388, 0.642]) indicated a strong overall relationship, while the significant total indirect effect (β = 0.399, t = 7.10, p < 0.001, CI [0.288, 0.509]) confirmed that mediators explained a substantial part. The direct effect (β = 0.125, t = 2.01, p < 0.05, CI [0.015, 0.260]) and the indirect effects through Emotional Valence (β = 0.180, t = 4.22, p < 0.001, CI [0.109, 0.278]) and Cognitive Trust (β = 0.149, t = 3.24, p < 0.001, CI [0.066, 0.247]) were all significant. Emotional Valence and Cognitive Trust thus partially and complementary mediate the relationship Perceived Humanness and Product Attitudes.

Finally, the full path from Humanization to Product Attitudes was analyzed for serial mediation. Two indirect pathways were significant: Humanization → Warmth → Perceived Humanness → Cognitive Trust → Product Attitudes (β = 0.072, t = 2.69, p < 0.01, CI [0.031, 0.140]) and Humanization → Warmth → Perceived Humanness → Emotional Valence → Product Attitudes (β = 0.087, t = 2.87, p < 0.01, CI [0.042, 0.165]). The significant total indirect effect (β = 0.258, t = 3.28, p = 0.001, CI [0.113, 0.428]) confirmed the mediators' positive contribution. However, the total effect (β = 0.106, t = 0.90, p = 0.367, CI [-0.118, 0.339]) was insignificant. This result could be explained by the direct effect (β = -0.152, t = 1.69, p = 0.091, CI [-0.336, 0.024]), which was negative and close to significance. Together, these findings indicate competitive, partial mediation as the mediators' positive effects are potentially suppressed by a negative direct relationship.

In conclusion, the mediation analysis and the path coefficients of the indirect effects (see Table 5) demonstrate the diminishing effects of humanization throughout the model, ultimately leading to a negligible impact of Humanization on Product Attitudes. This aligns with the findings from the independent samples t-test (see Table 2), which revealed no significant difference in Product Attitudes between the group exposed to the humanized stimulus and the control group (M = 5.20 vs. 5.26, t = 0.23, p = 0.816).

5. Discussion and conclusion

Responding to the emergence of autonomous technologies and the research gap identified in the introduction, this thesis aims to provide meaningful insights about if and how technology humanization affects anthropomorphism, and about if and how anthropomorphism shapes consumer perceptions that drive attitudes and intentions, ultimately addressing the research question:

Does human-like technology design and anthropomorphism impact consumer perceptions of autonomous vehicles – and if so, how?

5.1. Discussion of results

5.1.1. Technology humanization's effects on anthropomorphism (H1–H2)

This study conceptualized perceived *humanness* as a higher-order construct resulting from human perceptions of distinctly human traits in technology, drawing on the work of Söderlund & Oikarinen (2021). This construct functioned as a specific, ultimate measure of anthropomorphism, avoiding past studies' measurement confusion, and allowing a detailed evaluation of what factors contribute to this phenomenon. The examined humanlike traits were selected based on what theory indicated could result from technology humanization and impact perceived humanness.

Notably, *warmth* was the only variable that benefitted from humanization (H1c) and also positively influenced humanness (H2c) – and thus translated humanization into anthropomorphism[6]. The positive impact of humanization is understandable as it allowed the car to communicate positive emotions and present itself as friendly, helpful, and sincere, demonstrating attributes commonly associated with warmth (Fiske et al., 2007). This aligns well with findings indicating how humanlike features are perceived as warmer than machinelike ones (Carpinella et al., 2017; Stroessner & Benitez, 2019; Hsieh & Lee, 2024). Consequently, it is reasonable that warmth then contributed to perceived humanness and anthropomorphization: The aspects of warmth charted by Fiske et al. (2007) are uniquely human, while the capability of emotionality, seen as a prerequisite for warmth, is described by Söderlund & Oikarinen (2021) as a "fundamental aspect of humanness".

While *morality* was positively affected by humanization (H1d), it did not impact perceived humanness (H2d). Similar to warmth, the car's humanlike design enabled it to express statements indicating that it could distinguish right from wrong, conveying that it had a capacity for morality (Goodwin et al., 2014). Nevertheless, the weak support for this hypothesis suggests that factors beyond humanization have a stronger

[6] Warmth's mediation of humanization–perceived humanness is explored in this section's conclusion.

influence on morality perceptions. Contradictory to findings of that morality is an uniquely human trait (Goodwin et al., 2014; Haslam, 2006) that positively impacts perceived humanness (Söderlund & Oikarinen, 2021), this was not the case in this experiment. Potentially, morality's effects could be mediated as it is argued to be an aspect of warmth (Fiske et al., 2007), but such inter-capability associations are beyond this study's scope. As the authors, we wonder if consumers' growing familiarity with autonomous technology could cause them to attribute morality to manufacturers rather than to technology itself. As such, morality would not be perceived as a humanlike trait of technology, but merely as a reflection of the human intent of its creators.

Neither of the more cognitively oriented variables *competence* and *agency* were influenced by humanization (H1a, H1b) nor affected perceived humanness (H2a, H2b). It was expected that humanization would enable the car to convey competence by demonstrating its ability to act on its intelligence (Fiske et al., 2007) and agency by articulating how it planned its actions in accordance with its goals (H. M. Gray et al., 2007). For instance, Waytz et al. (2014) found that a humanized vehicle was perceived as more "smart", "anticipating", and "planning", while studies have shown humanlike technology perceived as more competent (Carpinella et al., 2017) and agentic (H. Y. Kim & McGill, 2018). However, this study did not find any such effects of humanization. The findings also contradict expectations that competence or agency foster perceptions of the technology having an mind of its own and thereby increasing perceived humanness (Epley et al., 2007; H. M. Gray et al., 2007; Waytz et al., 2014; Epley, 2018; Söderlund & Oikarinen, 2021).[7] One possible explanation could be the inflation of language: terms like "smart" are today often used to describe connected technology rather than unique attributes of conscious minds. Consumers might have learned that similar claims – even when made by the technology itself – are not any indications of humanness.

Lastly, *creepiness* was also not found to result from humanization (H1e). This contrasts with the Uncanny Valley theory (Mori et al., 2012) and prior findings that humanlike design of nonhuman entities can evoke feelings of creepiness and other unpleasant emotions (Castelo et al., 2019; K. Gray & Wegner, 2012; W. Kim et al., 2024; Mara et al., 2022; Mende et al., 2019). However, the Uncanny Valley effect is expected to be non-linear, and the experiment's humanized car might not have been perceived as sufficiently humanlike to be considered creepy. While the effects of creepiness on perceived humanness did not fully support the hypothesis (H2e), they were close to significance and indicated a negative effect ($p = 0.06$; $\beta = -0.131$). This suggests that perceived creepiness could stem from personal characteristics rather than humanization, and that creepiness might still impair perceptions of humanness.

[7] It is important to clarify that the study's PLS-SEM model calculates independent path coefficients for all links in the structural model. Consequently, although humanization did not affect competence and agency, the variables competence and agency could still influence humanness, if driven by other factors.

Concluding this section, it is noteworthy that warmth emerged as the single humanlike trait that fully mediated the relationship between humanization and perceived humanness (see section 4.3) – perhaps warmth contributes most to "the perception of a humanlike mind" (Epley, 2018)? However, although the humanization–warmth–humanness path had a strong indirect effect ($\beta = 0.483$), only half of the variance of humanness was explained ($R^2 = 0.517$), suggesting that the perception of humanness is influenced by several unmeasured factors. Furthermore, warmth's low explained variance ($R^2 = 0.176$) indicated that further unaccounted factors beyond humanization affect initial perceptions of warmth, which then affects humanness. This aligns with theory suggesting that individual psychological determinants profoundly impacts anthropomorphism (Epley et al., 2007; Epley, 2018). Consequently, technology humanization appears far from the only source of anthropomorphism – and potentially as a limited one – and anthropomorphism thus seems highly challenging to control.

5.1.2. Anthropomorphism's primary outcomes on cognitive and affective trust, emotional valence, and perceived risks (H3)

Before discussing the primary outcomes of anthropomorphism, it is important to clarify that these effects arise from anthropomorphism regardless of antecedents and should therefore not be attributed only to technology humanization[8]. The full effects of humanization throughout the model will be addressed when concluding the discussion.

As anthropomorphism entails perceiving technology as possessing human qualities – such as understandable, humanlike minds that are capable of thinking and feeling, and with the capacity to be competent, responsible, and social (Epley et al., 2007; Waytz et al., 2014; Epley, 2018) – it was hypothesized that anthropomorphism would increase cognitive and affective trust, positive emotional valence, and lower perceived risks. All of these hypotheses were confirmed by the study results and are discussed below.

The findings show that anthropomorphism indeed increased several aspects of trust in the technology, concurring with a vast number of empirical studies (e.g., Hancock et al., 2011; Waytz et al., 2014; van Pinxteren et al., 2019; de Visser et al., 2016; Glikson & Woolley, 2020; Lee & Chen, 2022; Schreiter et al., 2022). First, anthropomorphism's positive impact on *cognitive trust* (H3a) can be understood, as that which is perceived human is also perceived as more competent (Waytz et al., 2014) and agentic (H. M. Gray et al., 2007; H. Y. Kim & McGill, 2018), and can therefore be expected to be trusted to perform more reliably. Second, its positive influence on *affective trust* (H3b) can be explained by how anthropomorphism enables humans to relate to nonhuman entities as social persons (Epley et al., 2007), presumably capable of forming

[8] This is true for the entire model, and please revisit the previous paragraph for examples. The step-by-step nature of the PLS-SEM analysis allows variables to simultaneously function as both independent and dependent variables, enabling the analysis of all subsequent effects, independent of antecedents. This is explained further in Section 3.6.

interpersonal emotional bonds, and such social presence and attraction has been shown to enhance affective trust (J.-G. Lee et al., 2015; Q. Q. Chen & Park, 2021).

Anthropomorphism's positive association with *emotional valence* (H3c) was anticipated for similar reasons. As anthropomorphism enables nonhuman entities to be perceived as social, such entities can also be perceived to have emotions (Epley et al., 2007). Through the empathic social process of emotional contagion, humans tend to adopt the emotions of those around them (Hatfield et al., 1993). Perceived humanness has been shown to foster empathy, enabling positive emotions of nonhuman beings to influence humans to experience positive emotions themselves (Liu et al., 2024). The findings thus suggest that perceived humanness of nonhuman entities, evoked – at least in part – by displays of positively valanced emotions, can induce positive emotions in humans.

The findings further indicate that anthropomorphism decreases *perceived risks* (H3d). Perceived risks primarily arise from uncertainty (Ribeiro et al., 2022) and are particular concerning for autonomous vehicles (Othman, 2021). One driver of anthropomorphism is the human desire to interact efficiently with the environment by reducing uncertainty – and entities perceived as human are easier to explain, predict, and control (Epley, 2018; Epley et al., 2007). Consequently, as anthropomorphism helps decrease uncertainty, it is reasonable that it reduces perceived risks. These results aligns with previous studies suggesting that anthropomorphism influences risk perceptions (Cui, 2022; S. Kim & Mcgill, 2011).

5.1.3. Downstream effects on product attitudes and intentions (H4–H5)

Considering the effects of these four variables on product attitudes, it was surprising that only cognitive trust and emotional valence had positive impacts on participants' overall attitudes regarding the study's autonomous vehicle.

Cognitive trust's positive impact on product attitudes (H4a) was expected, as rational evaluations of a product's reliable and dependable performance are considered central to forming attitudes towards technology (Kulviwat et al., 2007; Venkatesh & Davis, 2000; Venkatesh et al., 2003). The beneficial effect of *emotional valence* (H4c) on product attitudes can be explained by affect infusion: products eliciting positive emotions enhance consumers' affective states which then influence subsequent product evaluations (Forgas, 1995). Additionally, positive affect is seen as an antecedent to technology attitudes (Kulviwat et al., 2007). Combined, these findings support the established notion that cars are evaluated primarily through high-involvement (cognitive) and transformational (emotional) standards (Rossiter et al., 1991).

Contrary to expectations, *affective trust* did not influence product attitudes (H4b). It had been hypothesized that this would result in positive affect and benefit product attitudes through similar mechanisms as emotional valence. This was not the case, highlighting the importance of fully exploring downstream effects on key dependent variables.

Surprisingly, the results also did not show that that *perceived risks* affected product attitudes (H4d), despite risks being considered as a highly relevant factor influencing the adoption of autonomous vehicles (Othman, 2021; Rezaei & Caulfield, 2020; Schoettle & Sivak, 2014, 2015). This goes against theories regarding risk as negatively associated with consumer preferences (Mitchell, 1992) and humans as generally loss-averse (Kahneman & Tversky, 1979; Levy, 1992). For this study's participants – risk does not seem to matter at all. However, we wonder if this might be due to the experiment situation, and this will be discussed further in limitations (see section 5.3).

Interestingly, a non-hypothesized positive direct relationship between *perceived humanness–product attitudes* was found, although with a fairly weak effect ($\beta = 0.125$). This effect can be understood as humans often exhibit a positive charge towards other humans (Sears, 1983, as cited in Söderlund & Oikarinen, 2021), likely resulting from evolutionary social processes, which is supported by findings that mere human presence in physical stores (Söderlund, 2016) or perceived humanness of technology (Söderlund & Oikarinen, 2021) can elicit positive emotions and satisfaction among consumers.

Combined, these variables explained approximately 70% of the variance in product attitudes ($R^2 = 0.699$), with emotional valence ($\beta = 0.387$) cognitive trust ($\beta = 0.324$) contributing the most, while the direct effect of perceived humanness played a minor part ($\beta = 0.125$). Given this strong explanatory power, the results provide valuable insights for makers and marketers of autonomous vehicles on key areas to prioritize to drive adoption. However, many unmeasured antecedents to these variables exist beyond anthropomorphism. The full impacts of anthropomorphism and humanization on product attitudes will be discussed in the next section, which concludes the discussion.

Nevertheless, product attitudes positively influenced *intentions to use* (H5), with a strong effect explaining approximately 66% of its variance ($\beta = 0.814$, $R^2 = 0.662$). While this relationship is so widely accepted within marketing that it is often used to establish the nomological validity of attitude measures, the items in this study's intention measure (Appendix F) indicate that those with positive overall attitudes toward the car were also more positive about using its autonomous features.

5.1.4. Ultimate impacts of anthropomorphism and humanization on product attitudes

To fully address the study's research question, three steps must be considered: (1) the impact of humanization on anthropomorphism; (2) the influence of anthropomorphism on product attitudes; and, ultimately, (3) the mediated effects of humanization on product attitudes through anthropomorphism.

First, the conclusion of section 5.1.1 established that technology humanization seems to have a limited impact on anthropomorphism, which instead appeared to be affected by several unmeasured sources – and anthropomorphism therefore emerged as highly difficult to control.

Second, the mediation analysis (section 4.3) showed that anthropomorphism's effects on product attitudes were partially and complementary mediated by Cognitive Trust (β = 0.149) and Emotional Valence (β = 0.180), with a direct effect also contributing to the impact (β = 0.125). Aligned with a vast number of studies, these findings indicate that anthropomorphism indeed has a beneficial impact on product attitudes – albeit a fairly modest one. However, if anthropomorphism is largely beyond the influence of technology design or marketing efforts as indicated earlier – does anthropomorphism's beneficial effects matter in practice, if it cannot be controlled to begin with?

Furthermore, anthropomorphism's primary outcomes (section 5.1.2) only explained approximately 21% of the variance in cognitive trust (β = 0.416, R^2 = 0.221) and emotional valence (β = 0.464, R^2 = 0.215). Accordingly, many unmeasured factors contributed to the variables that led to a majority of the effects on product attitudes. Exploring these antecedents may thus be a higher priority for those desiring to drive technology adoption, rather than attempts at inspiring anthropomorphism.

Third, and finally, considering mediation throughout the entire model (section 4.3): while humanization has slight indirect effects on product attitudes, serially mediated by warmth, perceived humanness, and cognitive trust (β = 0.072) or emotional valence (β = 0.087), its ultimate effects are marginal. The presence of an unexpected negative direct effect, close to significance, indicates competitive mediation that could diminish these effects even further. Consequently, technology humanization does not appear to benefit consumers' attitudes towards autonomous vehicles.

5.2. Conclusions and implications

5.2.1. Main findings

This thesis examined if and how humanlike technology design and anthropomorphism impacts consumer perceptions of autonomous vehicles, specifically regarding product attitudes and subsequent intentions to use.

Technology humanization's effect on anthropomorphism (i.e., perceived humanness) was fully mediated by participants' perceptions of *warmth*. Contrary to what theory proposed, neither perceived *competence*, *agency*, or *creepiness* was affected by humanization nor influenced anthropomorphism. Perceived *morality* benefitted from humanization but did not impact perceived humanness. The findings further suggest that many unmeasured antecedents beyond technology humanization influence both warmth and subsequent perceptions of humanness, making anthropomorphism highly challenging to affect or control.

As predicted by theory and prior studies, anthropomorphism – regardless of antecedents – had beneficial effects on *cognitive trust*, *affective trust*, *emotional valence*, and *perceived risks*. However, out of these variables, only cognitive trust and emotional

valence significantly impacted *product attitudes*. Together with a minor direct effect attributed to humanness' inherent positive charge, cognitive trust and emotional valence mediated anthropomorphism's modest, but not unsubstantial, effect on product attitudes. Nevertheless, if anthropomorphism cannot be controlled – it is questionable what value this effect has in practice.

Considering the full chain of effects throughout the entire model, the ultimate effects of technology humanization on product attitudes as mediated by anthropomorphism were negligible. Accordingly, technology humanization did not seem to influence consumers' attitudes towards autonomous vehicles.

As expected according to theory and a vast number of studies, product attitudes had a positive effect on participants *intentions to use*, which in this study specifically regarded intentions towards using the car's autonomous features. Nevertheless, this effect is contingent on the ability to influence product attitudes.

In summary, technology humanization does not seem to matter for consumers' attitudes or use intentions regarding autonomous vehicles. And while anthropomorphism matters to some extent – it appears largely beyond the control of technology manufacturers and marketers.

5.2.2. Theoretical implications

The findings of this study contribute to the theoretical understanding of technology humanization and anthropomorphism in several ways. The study's comprehensive theoretical framework and resulting model demonstrates that charting the full chain of effects from humanization to anthropomorphism to key downstream variables is vital for fully understanding the impact of these phenomena on consumer attitudes and technology adoption intentions. The step-by-step assessment of the model also shows how anthropomorphism can indeed contribute to effects such as enhanced affective trust or reduced perceived risks – without any assumed subsequent benefits on consumers' overall product attitudes. Consequently, this problematizes the fragmentation of the research in the field, with the implication that holistic models and compatible measures are needed to fully comprehend the potential impacts of humanization and anthropomorphism.

Furthermore, while the findings support Söderlund & Oikarinen's (2021) notion of perceived humanness as a higher-order construct emerging from distinctly human characteristics, the fact that neither perceived competence, agency, nor morality influenced perceived humanness in the study raises an important question: what attributes are currently regarded as uniquely human? Epley (2018) argued that factors contributing to the perception of a humanlike mind are most essential for anthropomorphism. The study's findings suggest that these factors may be changing.

Considered in the light of the wide emergence of autonomous technologies in society, this could have important implications for the field's theoretical development.

5.2.3. Practical implications

The introduction posed the question: "why are not self-driving cars extensively humanized"? However, as authors, we suspected that autonomous vehicle manufacturers might have valid reasons for their design decisions that are not publicly disclosed through published research. As mentioned, this study's practical implications are clear: technology humanization does not significantly influence consumer attitudes or intentions to use autonomous vehicles, and the primary drivers of anthropomorphism seem beyond the reach of technology design or marketing strategies. Consequently, automotive companies should prioritize other areas to drive consumer preferences regarding self-driving cars.

Nevertheless, the findings support and extend established theories related to car marketing and technology adoption. As cognitive trust and emotional valence are found to be the most potent drivers of product attitudes towards self-driving cars, this reinforces the established notion of cars as high-involvement and transformational purchases (Rossiter et al., 1991) and extends it to include autonomous vehicles. This suggests that marketing efforts should continue emphasizing performance attributes that can enhance cognitive evaluations in combination with branding and design elements that can foster emotional valence. Additionally, the study confirms that overall attitudes toward the car strongly influence consumers' intentions of using its autonomous features. Accordingly, the practical implications suggest that makers and marketers of self-driving cars should continue to focus on established, effective approaches.

5.3. Limitations and suggestions for future research

5.3.1. Increasing experimental realism

While text-based scenario studies followed by self-reporting questionnaires are widely established within social sciences (see section 3.1), there is, naturally, a difference between responding to an online survey about an imaginary commercial and sitting in a car being driven by an AI at 120 km/h. If participants were to personally experience a self-driving vehicle, the study results could be very different. Most likely, the risks perceived in this experiment weren't tangible enough. Risks could plausibly have a more significant and negative impact on product attitudes than was found in the current study. Further, it is uncertain whether somewhat more realistic stimuli such as driving simulators, used by Waytz et al. (2014), are sufficient to evoke genuine perceptions of risk, as in real-life scenarios where one's wellbeing is at stake. Future studies should attempt to maximize realism by exposing consumers to actual self-driving vehicles, while potentially also measuring physiological and behavioral reactions.

5.3.2. Examining anthropomorphism's effects over time

Within the study context, a longitudinal study was not possible due to time constraints. While we do not believe that results would change significantly within the short term, future studies should explore how responses change over time as consumers become increasingly accustomed to autonomous technologies. For instance, technology acceptance studies often include previous usage experience as moderators (Venkatesh et al., 2003; Venkatesh & Davis, 2000). While questions concerning previous experience of autonomous vehicles were asked in this thesis, few participants had such experience. As people get used to more advanced technologies such as autonomous vehicles, they might anthropomorphize them less because there are less perceived uncertainties (Epley et al., 2007). Therefore, future research should adopt longitudinal study designs to explore how repeated interactions influence the human tendency to anthropomorphize technology. Insights from such studies could enable marketers to determine whether anthropomorphism of technology is relevant in the future and provide strategic guidance for technology design developers.

5.3.3. Overcoming issues of self-reported measures

Self-reported questionnaires involve limitations. It is known that questionnaires may cause subjectivity or memory bias, which limits authenticity of participants' responses (J. Wu et al., 2024). Furthermore, self-reported responses might underestimate participants' tendency to anthropomorphize humanized vehicles as they only capture conscious reflections on humanized technology. They do not account for physiological reactions or behaviors evoked by human-like design. Thus, participants may report a low perceived humanness while their reactions and behavior demonstrate the opposite. As mentioned, future studies should therefore incorporate real-life stimuli and physiological or behavioral measures to fully understand the nuances of how people interact with humanized technology. Such studies could provide a more accurate representation of participants' anthropomorphic tendencies. Furthermore, future research could also include qualitative elements. By allowing participants to freely express their opinion about technology without being explicitly prompted to consider perceived humanness, their responses to humanized technology could be more genuine and offer novel insights.

Appendices

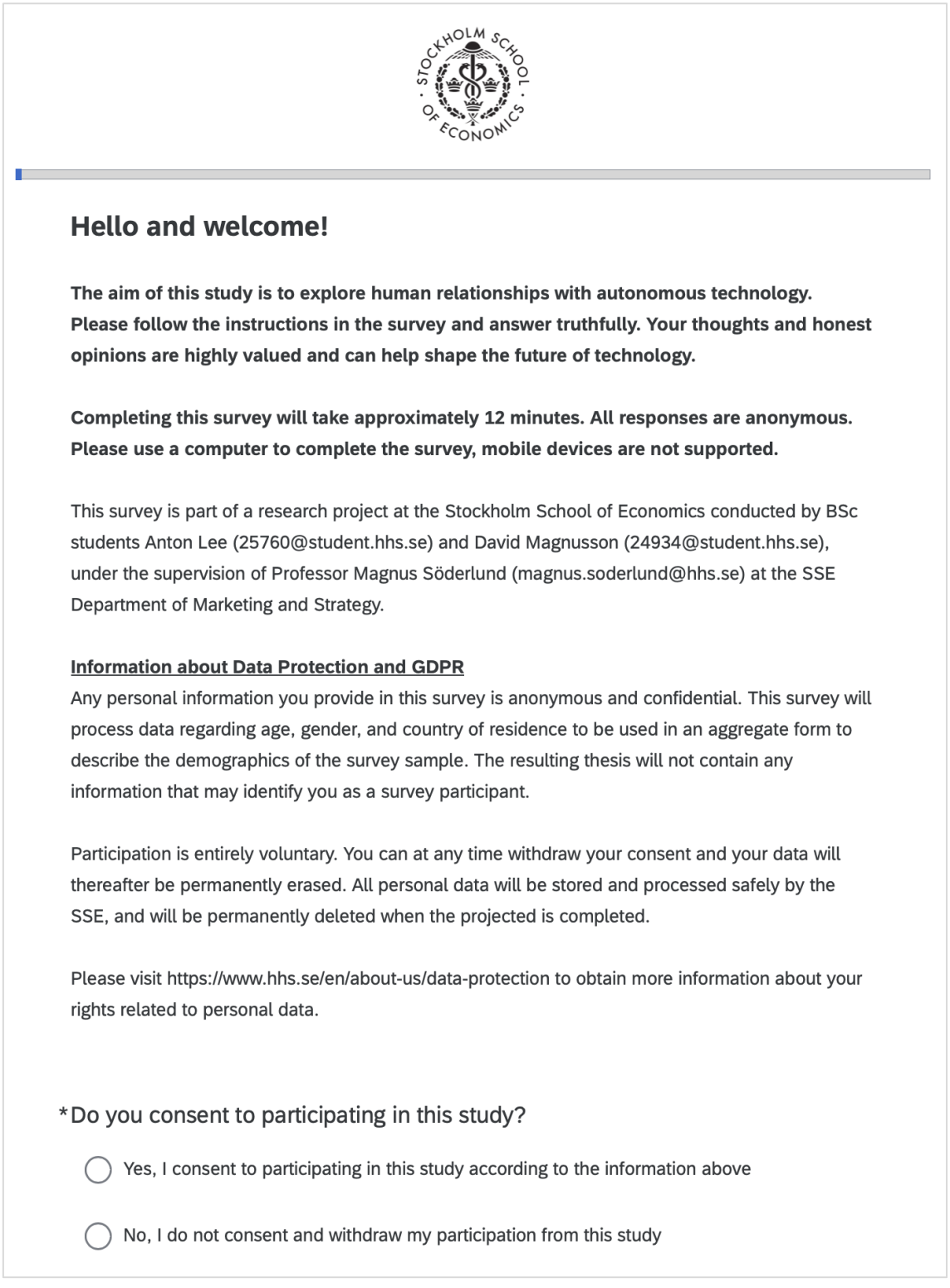
Appendix A: Hypotheses summary

Table 6. Summary of study hypotheses

Study hypotheses	
H1a	Technology humanization positively influences perceived competence
H1b	Technology humanization positively influences perceived agency
H1c	Technology humanization positively influences perceived warmth
H1d	Technology humanization positively influences perceived morality
H1e	Technology humanization positively influences perceived creepiness
H2a	Perceived competence positively influences perceived humanness
H2b	Perceived agency positively influences perceived humanness
H2c	Perceived warmth positively influences perceived humanness
H2d	Perceived morality positively influences perceived humanness
H2e	Perceived creepiness negatively influences perceived humanness
H3a	Perceived humanness positively influences cognitive trust
H3b	Perceived humanness positively influences affective trust
H3c	Perceived humanness positively influences emotional valence
H3d	Perceived humanness negatively influences perceived risks
H4a	Cognitive trust positively influences product attitudes
H4b	Affective trust positively influences product attitudes
H4c	Emotional valence positively influences product attitudes
H4d	Perceived risks negatively influence product attitudes
H5	Product attitudes positively influence intentions to use

Appendix B: Survey introduction, GDPR, informed consent

Survey introduction, data protection and GDPR, and informed consent



Hello and welcome!

The aim of this study is to explore human relationships with autonomous technology. Please follow the instructions in the survey and answer truthfully. Your thoughts and honest opinions are highly valued and can help shape the future of technology.

Completing this survey will take approximately 12 minutes. All responses are anonymous. Please use a computer to complete the survey, mobile devices are not supported.

This survey is part of a research project at the Stockholm School of Economics conducted by BSc students Anton Lee (25760@student.hhs.se) and David Magnusson (24934@student.hhs.se), under the supervision of Professor Magnus Söderlund (magnus.soderlund@hhs.se) at the SSE Department of Marketing and Strategy.

Information about Data Protection and GDPR

Any personal information you provide in this survey is anonymous and confidential. This survey will process data regarding age, gender, and country of residence to be used in an aggregate form to describe the demographics of the survey sample. The resulting thesis will not contain any information that may identify you as a survey participant.

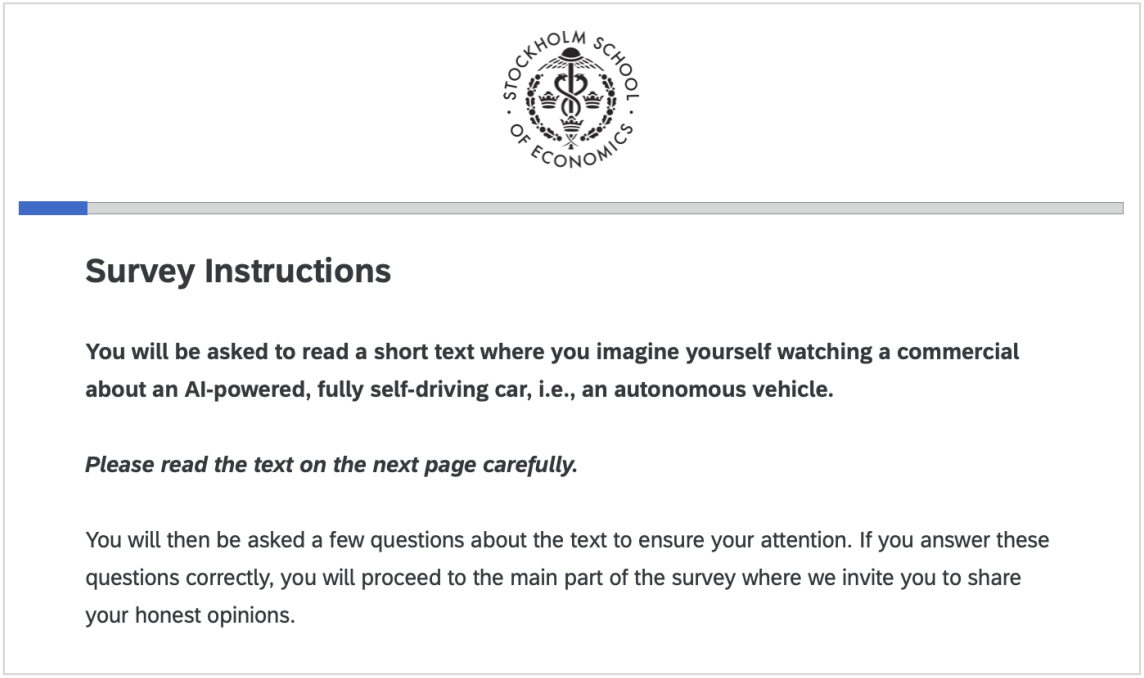
Participation is entirely voluntary. You can at any time withdraw your consent and your data will thereafter be permanently erased. All personal data will be stored and processed safely by the SSE, and will be permanently deleted when the projected is completed.

Please visit https://www.hhs.se/en/about-us/data-protection to obtain more information about your rights related to personal data.

*Do you consent to participating in this study?

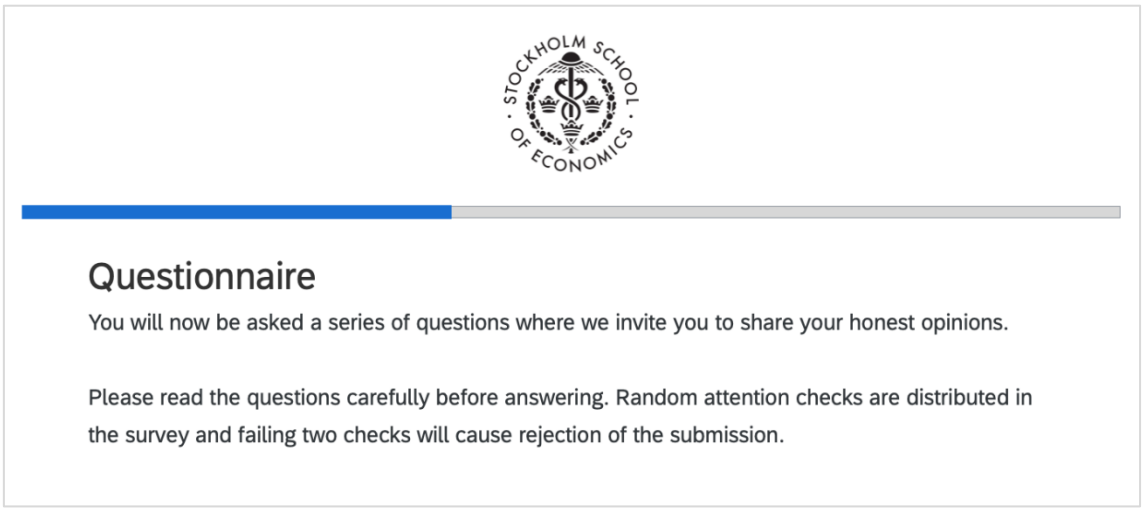
- ◯ Yes, I consent to participating in this study according to the information above
- ◯ No, I do not consent and withdraw my participation from this study

Survey instructions

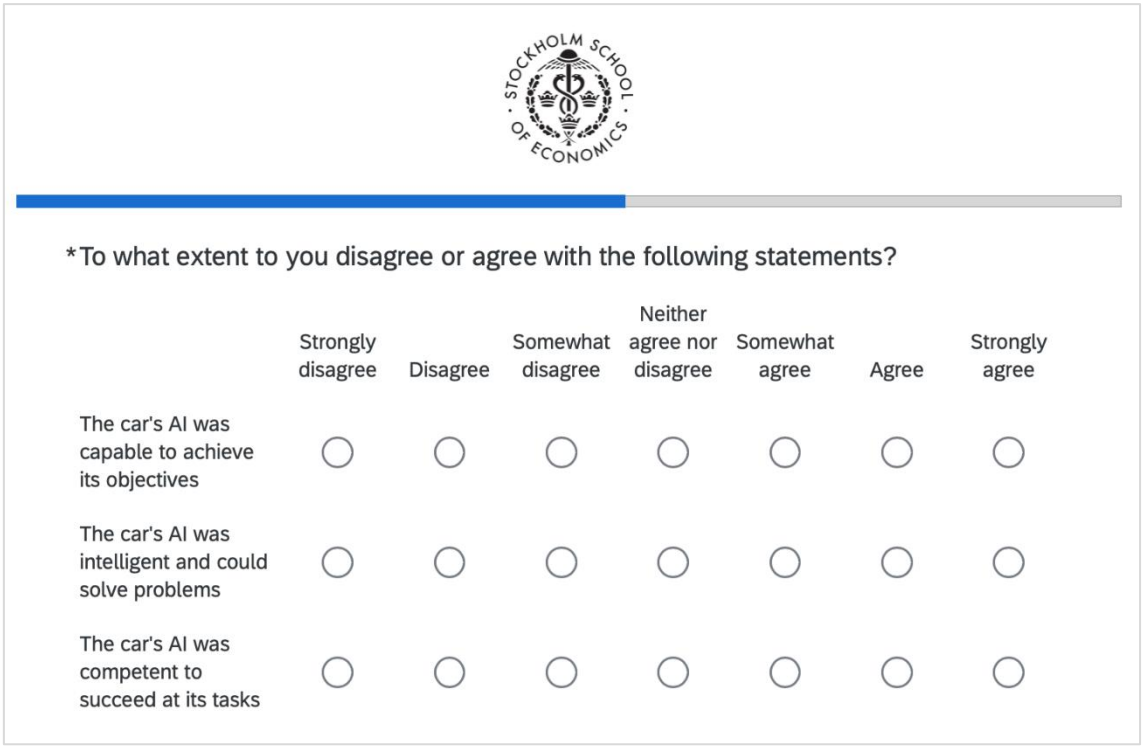


Note: The study's experimental stimuli and the comprehension, attention and manipulation checks are available in full in the following appendices.

Questionnaire instructions



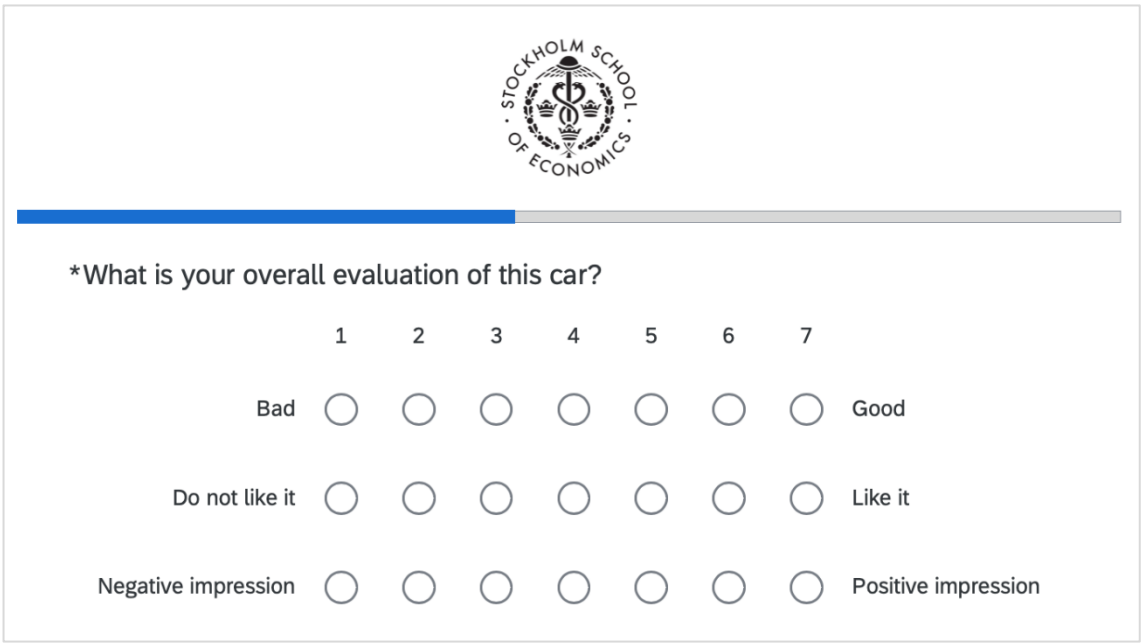
Likert scale question example



*To what extent to you disagree or agree with the following statements?

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
The car's AI was capable to achieve its objectives	○	○	○	○	○	○	○
The car's AI was intelligent and could solve problems	○	○	○	○	○	○	○
The car's AI was competent to succeed at its tasks	○	○	○	○	○	○	○

Sematic differential scale question example



*What is your overall evaluation of this car?

	1	2	3	4	5	6	7	
Bad	○	○	○	○	○	○	○	Good
Do not like it	○	○	○	○	○	○	○	Like it
Negative impression	○	○	○	○	○	○	○	Positive impression

Appendix C: Experimental stimuli

Blue text represents stimuli differences, while black text was constant for both groups.

Stimulus 1: Tesla Iris (humanized)

Imagine you are watching a commercial for a self-driving car. It begins on a beautiful early morning, with a person walking up to a car that stands ready, engine running, on the street outside their front door. As the person approaches, the car door automatically opens, and the advertisement voice-over says:

"As the first completely autonomous AI-powered vehicle, the fully self-driving Tesla Iris is your personal driver that is always ready to take you where you want to go."

The person sits in the driver's seat and a display shows a face that begins to smile when making eye-contact with the person, followed by a female voice in the speakers that says:

"Hi, I'm Iris! I'm so happy to be driving you. Where would you like us to go today?". The person answers: "Take me to the city center", and Iris replies:
"Fun! It's been a long time since we went downtown, I've been looking forward to it!

The steering wheel turns on its own as Iris drives out into traffic. Iris navigates rush-hour traffic by changing lanes and planning her route, stopping for red lights and pedestrians, before accelerating onto the highway. She passes several slower drivers and maintains a speed of 70 mph.

The sun rises over the landscape along the highway. Iris says: "It's a beautiful morning, are you excited about going downtown together?". The person yawns and replies, "I'd like to go back to bed!" Iris looks at the person with understanding. "I'm sorry you're feeling tired. Should we listen to some music to wake you up?" The person agrees and smiles as upbeat music starts playing.

As traffic increases, Iris says "I heard that there will be more traffic than expected. I can get us downtown ten minutes faster and save energy, so let's take the better route!", and changes lanes towards the new route.

The advertisement voice-over explains: "Powered by groundbreaking AI algorithms trained on billions of miles of real-world data, Tesla Iris gets you to your destination safer, faster, and more energy efficient than any human driver."

While cruising on the highway, another driver suddenly swerves across lanes and comes

very close to crashing into the car. Iris' face looks concerned, she immediately honks the horn, brakes to slow down, and avoids the collision. Iris' expression turns happy and calm as she looks at the person and says: "Wow, that was clearly not an AI-powered car! I'm just happy no one got hurt. Don't worry, I'm keeping all of us safe!"

Iris arrives at the city center and smoothly parks in a tight spot. Iris says: "We're here! Hope you have fun downtown. I'll hang out here until we're ready to go home".

The person exits the car; the camera zooms out and shows the vibrant city streets as the Tesla Iris logo is displayed. The advertisement ends.

Stimulus 2: Tesla Model A (non-humanized)

Imagine you are watching a commercial for a self-driving car. It begins on a beautiful early morning, with a person walking up to a car that stands ready, engine running, on the street outside their front door. As the person approaches, the car door automatically opens, and the advertisement voice-over says:

"As the first completely autonomous AI-powered vehicle, the fully self-driving Tesla Model A is the car that is always ready to take you where you want to go."

The person sits in the driver's seat and a display shows a map and the text "Select destination".

The person touches the location of the city center on the map. A suggested route is displayed, and the person agrees by tapping the button marked "Drive to destination". The car's AI confirms by displaying the message "Driving to destination".

The steering wheel turns on its own as Model A drives out into traffic. The car's AI navigates rush-hour traffic by changing lanes and planning its route, stopping for red lights and pedestrians, before accelerating onto the highway. The car passes several slower cars and maintains a speed of 70 mph.

The sun rises over the landscape along the highway. The car's display reads, "Driving downtown" and shows a box titled "Suggested music for a beautiful morning" with playlists of recommended music. The person yawns, selects the playlist "Wake me up!" and smiles as upbeat music starts playing.

As traffic increases, the display shows "Replanning route due to expected traffic". The map is updated, the estimated time of arrival and energy consumption is decreased, and the car changes lanes towards the new route.

The advertisement voice-over explains: “Powered by groundbreaking AI algorithms trained on billions of miles of real-world data, Tesla Model A gets you to your destination safer, faster, and more energy efficient than any human driver.”

While cruising on the highway, another driver suddenly swerves across lanes and comes very close to crashing into the car. The car’s display flashes, signaling potential danger. The car’s AI immediately honks the horn, brakes to slow down, and avoids the collision. The display states: “Collision avoided: passenger safety ensured”.

The car arrives at the city center and smoothly parks in a tight spot. The display states: “Arrived at destination”.

The person exits the car, the camera zooms out and shows the vibrant city streets as the Tesla Model A logo is displayed. The advertisement ends.

Appendix D: Comprehension, attention, and manipulation checks

Comprehension checks

Instructions: “Based on the text you just read, please answer the questions below. Please re-read the text above if you are unsure. You will have two opportunities to answer these questions correctly.”

Q1: What happened when the person entered the car?

- The car looked at the person, smiled, and asked “Where would you like us to go today?” **[Correct for Tesla Iris]**
- The car displayed a map with the option to “Select destination” **[Correct for Tesla Model A]**
- The person pressed a button to activate the car's self-driving features

Q2: How did the person enter their destination?

- By tapping the map on the screen **[Correct for Tesla Model A]**
- By saying it out loud **[Correct for Tesla Iris]**
- By typing the destination manually

Q3: What happened after the potential collision on the highway?

- The car accelerated quickly to pass the other vehicle
- The display showed the message “Collision avoided” **[Correct for Tesla Model A]**
- The car reassured the person by saying “I’m just happy that no one got hurt” **[Correct for Tesla Iris]**

Attention checks

7-point Likert scale, ranging from strongly disagree (1) to strongly agree (7).

- *Q1: To ensure that you are paying attention, please select "Strongly disagree" for this statement* **[Correct alternative: Strongly disagree]**
- *Q2: To confirm that you’re paying attention, please select “Somewhat agree” if you are reading this statement* **[Correct alternative: Somewhat agree]**

Manipulation check

7-point Likert scale, ranging from strongly disagree (1) to strongly agree (7).

- *Q1: I perceived that the car's AI had a voice*
- *Q2: I perceived that the car's AI had a face*
- *Q3: I perceived that the car's AI had a human name*
- *Q4: I perceived that the car's AI was female*

Appendix E: Sample demographics

Table 7. Sample demographics

Experimental group	**Humanized Stimulus**		**Non-humanized Stimulus**		**Total Sample**	
	n = 93		*n* = 96		*n* = 189	
Variable	*n*	%	*n*	%	*n*	%
Gender						
Male	47	51%	45	47%	92	49%
Female	46	49%	51	53%	97	51%
Non-bin./Prefer not to say	0	0%	0	0%	0	0%
Age						
18-24	11	12%	14	15%	25	13%
25-34	28	30%	27	28%	55	29%
35-44	24	26%	27	28%	51	27%
45-54	16	17%	14	15%	30	16%
55-64	8	9%	7	7%	15	8%
65+	6	6%	7	7%	13	7%
Background						
Has a driver's license	79	85%	84	88%	163	86%
Has AV riding experience	11	12%	14	15%	25	13%
Has AV driving experience	5	5%	4	4%	9	5%

Appendix F: Study variables, items, and reliability and validity measures

Table 8. Study variables, items, and reliability and validity measures

Variable	Items	Factor loadings	CA	CR	AVE
Competence	The car's AI was intelligent and could solve problems	0.92	0.93	0.95	0.87
	The car's AI was capable to achieve its objectives	0.93			
	The car's AI was competent to succeed at its tasks	0.95			
Agency	The car's AI behaved as if it had clear goals	0.82	0.80	0.87	0.63
	It felt as if the car's AI had a mind of its own	0.79			
	The car's AI had the capacity to plan its actions	0.82			
	The car's AI appeared to have a motivation of its own	0.73			
Warmth	The car's AI was kind	0.94	0.96	0.97	0.86
	The car's AI was caring	0.94			
	The car's AI was friendly	0.90			
	The car's AI was warm	0.94			
	The car's AI was sociable	0.92			
Morality	The car's AI was capable of telling right from wrong	0.95	0.92	0.95	0.86
	The car's AI could understand positive and negative consequences of its behavior	0.90			
	The car's AI could distinguish between what is good and what is bad	0.94			
Creepiness	The car's AI was creepy	0.92	0.89	0.93	0.81
	The car AI's capabilities were scary	0.89			
	The car AI's capabilities made me worried	0.89			
Perceived Humanness	The car's AI behaved much like a human	0.97	0.95	0.97	0.92
	The car's AI was humanlike	0.95			
	The car's AI acted like humans typically do	0.95			
Cognitive Trust	I can see the benefits in AIs that can perform this kind of task better than humans	0.90	0.94	0.95	0.77
	AIs that can perform this kind of task could be useful	0.88			
	I believe this kind of AI can perform well	0.89			
	AI-driven cars will be more accurate than human-driven cars	0.89			
	AI-driven cars will make less mistakes than human-driven cars	0.87			
	AI-driven cars will provide more consistent performance than human-driven cars	0.82			
Affective Trust	I would trust the car's AI to keep me safe	0.95	0.94	0.96	0.89
	I would trust the car's AI to care about me	0.91			
	I would trust the car's AI to ensure my wellbeing	0.96			
Emotional Valence	What are your emotions if you think about the car? [Negative emotions–Positive emotions]	0.92	0.92	0.95	0.87
	What are your emotions if you think about the car? [Sad–Happy]	0.94			
	What are your emotions if you think about the car? [Bad mood–Good mood]	0.93			
Perceived Risks	I would not feel safe riding in an AI-driven car	0.95	0.93	0.96	0.88
	I feel that there are many risks involved with riding in an AI-driven car	0.91			
	I would feel vulnerable when riding in an AI-driven car	0.95			

Product Attitudes	What is your overall evaluation of this car? [Bad–Good]	0.96	0.97	0.98	0.93
	What is your overall evaluation of this car? [Dislike–Like]	0.97			
	What is your overall evaluation of this car? [Negative impression–Positive impression]	0.97			
Intentions to Use	If I had access to a car like this one, I would intend to use its AI self-driving capabilities	0.98	0.98	0.99	0.96
	If this was my car, I predict that I would use its AI self-driving capabilities	0.98			
	If I had the option, I would intend to use this car's AI self-driving features	0.98			

Appendix G: Collinearity statistics

Table 9. Collinearity statistics (VIF) for inner model relationships

Relationship	VIF
Agency → Perceived Humanness	2.14
Competence → Perceived Humanness	2.28
Creepiness → Perceived Humanness	1.54
Morality → Perceived Humanness	2.40
Warmth → Perceived Humanness	2.74
Affective Trust → Product Attitudes	3.43
Cognitive Trust → Product Attitudes	2.83
Emotional Valence → Product Attitudes	2.96
Humanization → Agency	1.00
Humanization → Competence	1.00
Humanization → Creepiness	1.00
Humanization → Morality	1.00
Humanization → Warmth	1.00
Humanization → Perceived Humanness	1.36
Humanization → Product Attitudes	1.10
Perceived Humanness → Affective Trust	1.00
Perceived Humanness → Cognitive Trust	1.00
Perceived Humanness → Emotional Valence	1.00
Perceived Humanness → Perceived Risks	1.00
Perceived Humanness → Product Attitudes	1.60
Perceived Risks → Product Attitudes	2.60
Product Attitudes → Intentions to Use	1.00

Appendix H: Survey feedback

Table 10. Survey feedback questions, descriptive statistics, and distribution of answers

Statement	***M***	***SD***	**min**	**max**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
The scenario presented in the text about the car was realistic	5.69	1.18	1	7	1%	1%	4%	4%	28%	37%	26%
The questions were clearly formulated	6.20	0.77	3	7	0%	0%	1%	3%	9%	50%	37%
The survey did not try to influence my answers in any direction	6.06	0.98	2	7	0%	1%	2%	5%	9%	48%	35%
The survey was meaningful	5.74	1.10	1	7	1%	2%	1%	8%	23%	41%	25%

Note: *n*=189. 7-point Likert Scale ranging from strongly disagree (1) to strongly agree (7).

Appendix I: Correlations of study variables

Table 11. Pearson's correlations for study variables

	Humanized Stimuli	Competence	Agency	Morality	Warmth	Creepiness	Humanness	Cognitive Trust	Affective Trust	Emotional Valence	Perceived Risks	Product Attitude	Intentions to Use	Manipulation Check
Humanized Stimuli	1	-.013	.159*	.259**	.418**	.061	.246**	.050	.056	.021	-.098	-.017	.037	.682**
Competence	-.013	1	.536**	.530**	.531**	-.543**	.448**	.716**	.619**	.606**	-.522**	.658**	.626**	.183*
Agency	.159*	.536**	1	.617**	.593**	-.179*	.460**	.352**	.393**	.351**	-.238**	.340**	.312**	.354**
Morality	.259**	.530**	.617**	1	.708**	-.353**	.565**	.388**	.519**	.399**	-.310**	.406**	.326**	.369**
Warmth	.418**	.531**	.593**	.708**	1	-.319**	.700**	.451**	.548**	.461**	-.362**	.462**	.412**	.515**
Creepiness	.061	-.543**	-.179*	-.353**	-.319**	1	-.344**	-.496**	-.603**	-.562**	.593**	-.571**	-.590**	-.059
Humanness	.246**	.448**	.460**	.565**	.700**	-.344**	1	.456**	.558**	.462**	-.392**	.506**	.446**	.339**
Cognitive Trust	.050	.716**	.352**	.388**	.451**	-.496**	.456**	1	.728**	.740**	-.683**	.752**	.784**	.242**
Affective Trust	.056	.619**	.393**	.519**	.548**	-.603**	.558**	.728**	1	.739**	-.733**	.716**	.774**	.214**
Emotional Valence	.021	.606**	.351**	.399**	.461**	-.562**	.462**	.740**	.739**	1	-.691**	.775**	.760**	.195**
Perceived Risks	-.098	-.522**	-.238**	-.310**	-.362**	.593**	-.392**	-.683**	-.733**	-.691**	1	-.613**	-.709**	-.238**
Product Attitude	-.017	.658**	.340**	.406**	.462**	-.571**	.506**	.752**	.716**	.775**	-.613**	1	.815**	.155*
Intentions to Use	.037	.626**	.312**	.326**	.412**	-.590**	.446**	.784**	.774**	.760**	-.709**	.815**	1	.173*
Manipulation Check	.682**	.183*	.354**	.369**	.515**	-.059	.339**	.242**	.214**	.195**	-.238**	.155*	.173*	1

Note: Two-tailed test. *p < .05. **p < .01. ***p < .001.

Appendix J: PLS-SEM results, graphical output

Figure 4. PLS-SEM results for the hypothesized model

Note: The figure presents path coefficients (β) with p-values in parenthesis on the connections, and R^2 values inside the constructs. Bold lines denote significant paths. Solid lines represent hypothesized paths, while dashed lines represent non-hypothesized paths.

Appendix K: Hypotheses test results

Table 12. Summary of hypotheses test results

Study hypotheses		Result
H1a	Technology humanization positively influences perceived competence	Not supported
H1b	Technology humanization positively influences perceived agency	Not supported
H1c	Technology humanization positively influences perceived warmth	Supported
H1d	Technology humanization positively influences perceived morality	Supported
H1e	Technology humanization positively influences perceived creepiness	Not supported
H2a	Perceived competence positively influences perceived humanness	Not supported
H2b	Perceived agency positively influences perceived humanness	Not supported
H2c	Perceived warmth positively influences perceived humanness	Supported
H2d	Perceived morality positively influences perceived humanness	Not supported
H2e	Perceived creepiness negatively influences perceived humanness	Not supported
H3a	Perceived humanness positively influences cognitive trust	Supported
H3b	Perceived humanness positively influences affective trust	Supported
H3c	Perceived humanness positively influences emotional valence	Supported
H3d	Perceived humanness negatively influences on perceived risks	Supported
H4a	Cognitive trust positively influences product attitudes	Supported
H4b	Affective trust positively influences product attitudes	Not supported
H4c	Emotional valence positively influences product attitudes	Supported
H4d	Perceived risks negatively product attitudes	Not supported
H5	Product attitudes positively influence intentions to use	Supported

Appendix L: PLS-SEM results used for mediation testing

Table 13. PLS-SEM results used for mediation testing

						95% C.I.	
Effect type	Path	*β*	*t*	*p*	Bias	2.5%	97.5%
Total	Humanization → Perceived Humanness	0.492	3.52	0.000	0.000	0.204	0.754
Direct	Humanization → Perceived Humanness	-0.032	0.29	0.775	0.001	-0.254	0.187
Total indirect	Humanization → Perceived Humanness	0.525	4.52	0.000	-0.001	0.295	0.754
Specific indirect	Humanization → Warmth → Perceived Humanness	0.483	4.63	0.000	0.000	0.295	0.703
Total	Perceived Humanness → Product Attitudes	0.525	8.07	0.000	-0.002	0.388	0.642
Direct	Perceived Humanness → Product Attitudes	0.125	2.01	0.045	-0.001	0.015	0.260
Total indirect	Perceived Humanness → Product Attitudes	0.399	7.10	0.000	-0.001	0.288	0.509
Specific indirect	Perceived Humanness → Emotional Valence → Product Attitudes	0.180	4.22	0.000	0.001	0.109	0.278
Specific indirect	Perceived Humanness → Cognitive Trust → Product Attitudes	0.149	3.24	0.001	0.000	0.066	0.247
Total	Humanization → Product Attitudes	0.106	0.90	0.367	0.003	-0.118	0.339
Direct	Humanization → Product Attitudes	-0.152	1.69	0.091	0.004	-0.336	0.024
Total indirect	Humanization → Product Attitudes	0.258	3.28	0.001	-0.002	0.113	0.428
Specific indirect	Humanization → Warmth → Perceived Humanness → Cognitive Trust → Product Attitudes	0.072	2.69	0.007	0.000	0.031	0.140
Specific indirect	Humanization → Warmth → Perceived Humanness → Emotional Valence → Product Attitudes	0.087	2.87	0.004	0.001	0.042	0.165

Appendix M: Full survey questionnaire

Table 14 presents the full questionnaire provided to survey participants, including variables not incorporated into the final study and therefore not discussed further. Unless otherwise noted in brackets, responses were collected using a 7-point Likert scale ranging from strongly disagree (1) to strongly agree (7), with the prompt: "To what extent do you disagree or agree with the following statements?"

Table 14. Full survey questionnaire

Section/Variable	Items
Survey Introduction/GDPR	[See Appendix B]
Informed Consent	Do you consent to participating in this study? [Yes, I consent to participating in this study according to the information above / No, I do not consent and withdraw my participation from this study]
ReCaptcha	Please verify that you are not a robot [ReCaptcha]
Survey Instructions	[See Appendix B]
Randomized Stimulus	[See Appendix C]
Comprehension Checks	What happened when the person entered the car? [See Appendix D] How did the person enter their destination? [See Appendix D] What happened after the potential collision on the highway? [See Appendix D]
Questionnaire Instructions	[See Appendix B]
Satisfaction (bipolar)	How satisfied do you believe you would be with this car if you would use it? [Dissatisfied–Satisfied] To what extent do you believe that this car would meet your expectations? [Below expectations–Above expectations] Imagine an offering perfect in every respect, how near or far from this ideal would you consider this car? [Very far from what is ideal–Very close to what is ideal]
Product Attitudes (bipolar)	What is your overall evaluation of this car? [Bad-Good] What is your overall evaluation of this car? [Dislike-Like] What is your overall evaluation of this car? [Negative impression-Positive impression]
Perceived Usefulness	AI-driven cars like this one will make the lives of humans better AI-driven cars like this one will make the lives of humans more convenient AI-driven cars like this one will make the lives of humans more comfortable
Intentions to Use	If I had access to a car like this one, I would intend to use its AI self-driving capabilities If this was my car, I predict that I would use its AI self-driving capabilities If I had the option, I would intend to use this car's AI self-driving features
Information Search Intentions	I would search for more information about this car if it was available in the market
Word-of-Mouth Positive Valence Intentions	I would speak positively about this car to others
Word-of-Mouth Recommendation Intentions	It would be very likely that I would recommend this car to others
Purchase Intentions	If I was in the market for a new car, I would intend to purchase this car if it was available

Willingness-to-Pay Intentions	If I was in the market for a new car, I would pay a price premium for this car
Attention Check 1	To make sure you're paying attention, please select "strongly disagree" for this statement
Acceptance of Others' Use	I would accept if others travelled in AI-powered self-driving vehicles
	I would be comfortable with sharing the road with AI-powered self-driving vehicles
	I would not have concerns if other people travelled in AI-powered self-driving vehicles
Competence	The car's AI was intelligent and could solve problems
	The car's AI was capable to achieve its objectives
	The car's AI was competent to succeed at its tasks
Agency	The car's AI behaved as if it had clear goals
	It felt as if the car's AI had a mind of its own
	The car's AI had the capacity to plan its actions
	The car's AI appeared to have a motivation of its own
Morality	The car's AI was capable of telling right from wrong
	The car's AI could understand positive and negative consequences of its behavior
	The car's AI could distinguish between what is good and what is bad
Warmth	The car's AI was kind
	The car's AI was caring
	The car's AI was friendly
	The car's AI was warm
	The car's AI was sociable
Humanness	The car's AI behaved much like a human
	The car's AI was humanlike
	The car's AI acted like humans typically do
Creepiness	The car's AI was creepy
	The car AI's capabilities were scary
	The car AI's capabilities made me worried
Attention Check 2	To confirm that you're paying attention, please select "Somewhat agree" if you are reading this statement
Cognitive Trust 1	AI-driven cars will be more accurate than human-driven cars
	AI-driven cars will make less mistakes than human-driven cars
	AI-driven cars will provide more consistent performance than human-driven cars
Ease of Use	It appears clear and understandable how to interact with the car's AI
	The car's AI seems to be easy to use
	It seems effortless to interact with the car's AI
Cognitive Trust 2	I can see the benefits in AIs that can perform this kind of task better than humans
	AIs that can perform this kind of task could be useful
	I believe this kind of AI can perform well
Emotional Trust	I would feel secure about relying on the car's AI
	I would feel comfortable about counting on the car's AI
	I would feel safe about trusting the car's AI
Affective Trust	I would trust the car's AI to keep me safe
	I would trust the car's AI to care about me
	I would trust the car's AI to ensure my wellbeing

Discomfort	AIs that can perform this kind of task better than humans make me uncomfortable AIs that can perform this kind of task goes against what I believe technology should be used for AIs that can perform this kind of task are unsettling
Perceived Risks	I would not feel safe riding in an AI-driven car I feel that there are many risks involved with riding in an AI-driven car I would feel vulnerable when riding in an AI-driven car
Digital Security Concerns	I would worry about using an AI-driven car because others might be able to access the system I would fear to use an AI-driven car as it could allow me to be monitored or tracked I would be concerned that an AI-driven car's system could be hacked or interfered with
Privacy Concerns	I would worry that the car's AI would collect personal data from me It scares me that the car's AI would measure personal data from me I would be worried that the car's AI would get personal information from me
Emotional Valence (bipolar)	What are your emotions if you think about the car? [Negative emotions–Positive emotions] What are your emotions if you think about the car? [Sad–Happy] What are your emotions if you think about the car? Bad mood–Good mood
Age	Please enter your age in number of years [##]
Gender	Please select your gender [Female / Male / Non-binary or third gender / Prefer not to say]
Driver's License	Do you have a driver's license? [Yes / No]
Personal Experience	Have you previously used a car's self-driving features yourself? [Yes / No] Have you ever been driven in a car where the driver used self-driving features? [Yes / No]
Hedonic Motivation	It would be fun to ride in a self-driving vehicle I would find it entertaining to be ride in a self-driving vehicle Being driven by a self-driving vehicle would be enjoyable
Social Influence	People whose opinions that I value would prefer that I use vehicles with self-driving features People in my social networks who would use vehicles with self-driving features have more prestige than those who don't People who influence my behavior would want me to use vehicles with self-driving features
Manipulation Check	I perceived that the car's AI had a voice I perceived that the car's AI had a face I perceived that the car's AI had a human name I perceived that the car's AI was female
Survey Quality	The scenario presented in the text about the car was realistic The questions were clearly formulated The survey did not try to influence my answers in any direction The survey was meaningful
Survey Feedback	Do you have any feedback or comments regarding the survey? (not required) [Text box]

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Disclosure of AI-tools

Approval for the usage of generative AI tools was granted by Magnus Söderlund as the thesis supervisor and course director.

1. What AI tools have been used and how?

Generative AI (ChatGPT 4.0) has been used for grammar, synonym, spelling and overall language checks, using the prompt “check submitted text for language, grammar and punctuation, maintain tone and style and never add or change any content”.

2. In what ways have these tools contributed to increasing the quality of the thesis?

ChatGPT 4.0 has contributed to this thesis by enhancing the clarity and flow of the text.

3. What potential risks were found using AI and what measures were taken to reduce these risks?

The prompt was sometimes misunderstood by ChatGPT 4.0 as it didn’t consider the context of the text being written. At times, this led to unfitting suggestions for language improvement. This risk was recognized from the beginning of writing the thesis. Therefore, suggested corrections were always checked thoroughly and discarded if they didn’t correspond with the purpose of the text.

4. What are the insights gained from using AI tools in the thesis writing process?

By using ChatGPT 4.0, insights on how to write more nuanced and specific language with increased variation in sentence structures was gained.