Computers in Human Behavior 147 (2023) 107870

Contents lists available at ScienceDirect

Computers in Human Behavior

journal homepage: www.elsevier.com/locate/comphumbeh

Right agent, wrong level of hedonism: How high (vs low) hedonic values in AI-performed tasks lead to decreased perceptions of humanlikeness, warmth, and less consumer support

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ARTICLE INFO

Handling Editor: Prof. Nicolae Nistor

Keywords:
Artificial intellgience
Agent-task incongruency
Machine schema
Human schema
AI'S warmth
Perceived humanlikeness

ABSTRACT

Reasons of reactions towards artificial intelligence (AI) performing hedonic tasks invites attention. This research argues that the reference of comparison to assess AI's suitability for the task shifts from machine schema to human schema as the hedonic value of the task increases, leading to the decrease in perceived humanlikeness, perceived warmth, and support for the AI, subsequently. Four studies, including a big data study on GitHub and three experiments, have shown that people are less supportive of AI and its creators when AI performs highly (vs low) hedonic tasks. This effect is mediated by the perceived humanlikeness of AI, since it affects AI's perceived warmth in a way that decreasing perceived humanlikeness when AI is assigned to the tasks with high (vs low) hedonic values decreases the perceived warmth of the AI. Decreased perceived warmth, in turn, lowers people's support for the AI and its creators. This serial mediation mechanism remains robust when AI's baseline humanlikeness increases, when the hedonic value of AI's method of performing the task, rather than the task itself is manipulated, and when the perceived competence and fairness are tested as alternative paths in parallel.

Credit author statement

Mehmet Yanit: Conceptualization, Methodology, Validation, Formal Analysis, Resources, Data Curation, Writing-Original Draft, Writing – Review & Editing, Visualization, Project Administration. Metehan Yanit: Conceptualization, Software, Data Curation, Writing-Original Draft. Fang Wan: Writing – Review & Editing.

1. Introduction

Recent years have witnessed an unprecedented surge in the field of Artificial Intelligence (AI), with new advancements being made on a daily basis. One notable example is the introduction of DALL-E by OpenAI in 2021, which revolutionized the world of digital art. This advanced AI program has the ability to create art pieces based on textual inputs, which caught the attention of the public and sparked a great deal of interest and curiosity about the potential of AI in the art world (Gonsalves, 2022). Following in the footsteps of DALL-E, many other companies have released their own AI software that can alter or create images based on user input, with the belief that the immense number of possibilities AI offers in creating art will entertain and attract customers. (e.g., Wonder Mobile App). However, not everyone is convinced that AI can truly create art. Some people severely reacted as they believe that AI's alleged "creativity" is a mere hoax and that it only uses existing art pieces without consent of their creators to derive their own pieces, thereby negating the idea of originality (Babbs, 2023). Similarly, Replika, a conversational AI, has caused great concern among researchers due to its erotic role-playing capabilities (Cole, 2023). The AI is blamed for luring people into fake one-sided relationships with an entity that only pretends to have consciousness and feelings.

Besides the authenticity of AI generated content (e.g., art, intimate conversations), AI's social awareness has also sparked controversy recently. The AI-generated 24-h show on Twitch, "Nothing, Forever," which was inspired by the popular comedy show Seinfeld, was banned from the platform due to the severe backlash it received for transphobic jokes thrown by the AI (Leffer, 2023). In yet another incident, Neuro-Sama, a Twitch streamer that is completely controlled by AI, made statements denying the holocaust in one of its live broadcasts, causing great controversy and negative public opinion regarding its capability to follow social norms (Gach, 2023).

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https://doi.org/10.1016/j.chb.2023.107870
Received 17 April 2023; Received in revised form 4 July 2023; Accepted 6 July 2023
Available online 12 July 2023
0747-5632/

To date, the existing literature on AI and its impact on society has provided various potential explanations for such negative events and reactions that have occurred. Scholars have highlighted people's lack of trust in algorithmic decision-making as a contributing factor to the reactions (Dietvorst, Simmons, & Massey, 2015). Others have emphasized the importance of AI's neglect of the unique contexts in which it operates (Longoni, Bonezzi, & Morewedge, 2019) and its tendency to reduce complex concepts to numerical terms (Lee, 2018). Additionally, the issue of AI's lack of fairness (Lee & Baykal, 2017) and objectivity (Castelo, Bos, & Lehmann, 2019) has also been widely discussed.

Upon further reflection on the aforementioned incidents, we observed that they transpired in settings where AI agents were engaged in hedonic tasks. These tasks, such as creating art, role-playing, or telling jokes, inherently aim to provide pleasure to the recipients, thus carrying a significant emotional component (Whitley, Trudel, & Kurt, 2018). As the hedonic intensity of tasks elevates—take, for example, ChatGPT composing a poem versus Google Search Engine finding a poem—the expectations for emotional benefits such as surprise, entertainment, and pleasure proportionally increase (Picot-Coupey, Krey, Huré, & Ackermann, 2021; Okada, 2005). Consequently, an agent executing these tasks should progressively fine-tune its responses to the emotional needs of the user as the hedonic value of the task intensifies (Chandra, Shirish, & Srivastava, 2022; Rapp, Curti, & Boldi, 2021).

However, there's a misconception resulting from the seamless performance of AI in fact-based tasks and its perceived objectivity and reliability: a somewhat imprudent reliance on AI for tasks that it may not be ideally suited for (Henestrosa, Greving, & Kimmerle, 2023). AI algorithms are increasingly being developed and tasked with jobs that may not align with their fundamental capabilities.

In this paper we argue that AI agents may fall short in handling highly hedonic tasks due to their inherent non-hedonic nature. Tasks requiring a subjective and emotional approach, such as content evaluation, are often viewed with less credibility and trust when executed by AI agents (Henestrosa et al., 2023).

Theoretically, our current research makes a significant contribution to the existing literature by examining the relationship between AI's assignment to tasks with differing hedonic qualities and people's reactions to such arrangements. The current research marks a significant departure from previous studies in the field. Earlier work examining AI agent's acceptability in certain asks primarily focused on examining people's reactions to AI agents in those tasks with varying levels of humanlikeness in their presentation (Chaves & Gerosa, 2018; De Angeli & Carpenter, 2005; De Angeli, Johnson, & Coventry, 2001; Kaplan & Haenlein, 2019). More recently, research has shifted towards investigating people's preferences between AI and human agents (Longoni & Cian, 2022) and between different AI agents that are anthropomorphized to different genders as male and female (Ahn, Kim, & Sung, 2022) in both utilitarian and hedonic contexts.

However, our research takes a different approach by arguing that AI inherently incorporates both human and nonhuman qualities. We delve into the investigation of how the hedonic value associated with tasks assigned to AI agents can influence their perceived humanlikeness. Moreover, we explore how altering perceptions of humanlikeness through this mechanism ultimately impacts the perceived warmth of the AI agent. These factors, in turn, significantly influence people's propensity to support both the agent itself and its creators.

From a managerial standpoint, the current research underscores the importance of assigning AI agents to tasks that are appropriate for their capabilities, in order to achieve maximum efficiency in their integration into tasks. Given the enormous potential impact of AI in marketing, which can generate up to $2.6 trillion in value globally annually, companies are highly motivated to substitute human performance with AI performance in many business areas (Kumar, Rajan, Venkatesan, & Lecinski, 2019). However, it is evident from current public opinion that people hold critical perceptions regarding the assignment of certain tasks to AI agents. This means that companies must carefully consider the impact of indifferently employing AI agents as it may lead to negative public reactions and a loss of support. Therefore, it is crucial for companies to explore how to use AI agents in the right tasks to avoid public disdain and gain support.

2. Literature review

2.1. AI in tasks with high hedonic values

We claim that AI's assignment to highly hedonic tasks causes an agent-task incongruency for users and leads to negative opinion. In this line, prior work has examined the impact of congruency between a product and the domain in which it is used. For instance, research has shown that when a product offers a utilitarian benefit, the utilitarian ethical attribute contributes more to perceived product quality, resulting in improved product evaluations (Bodur, Duval, & Grohmann, 2015). Similarly, the congruency between the product type and sales promotion has been found to have a profound effect on the effectiveness of sales promotions (Chandon, Wansink, & Laurent, 2000) and product-benefit (uiliarian vs. hedonic) congruency has been shown to increase consumers' liking of a product (Mandler, 1981, pp. 3–36; Meyers-Levy & Tybout, 1989). Strahilevitz and Myers (1998) found that nonmonetary promotions are more effective when congruent hedonic products are offered. Focusing on effect of incongruency, Lee and Chu (2021) and Gill (2008) demonstrated that the addition of utilitarian attributes to hedonic-dominant products can result in lower evaluations of product combinations, since utilitarian-dominant products have functional and quality-related elements, while hedonic-dominant products have social and emotional elements (Prebensen & Rosengren, 2016).

Despite the plethora of research in product-product and product-domain congruency, The scarcity of research on agent-task congruency highlights a gap in understanding the effect of assigning AI agents in hedonic and utilitarian tasks (Ahn et al., 2022; Longoni & Cian, 2022). We argue that the utilitarian nature of AI agents creates an agent-task incongruency when they are assigned to perform hedonic tasks, which may lead to negative user evaluations. This is because AI agents are predominantly utilitarian and rely more on facts, rationality, and logic than social and emotional cues, which are essential in hedonic tasks (Longoni & Cian, 2022). The existing research provides support for this idea, as it shows that AI's utilitarian attributes are more prominent in various contexts. For instance, virtual assistants are primarily perceived for their utilitarian benefits rather than hedonic ones (McLean, Osei-Frimpong, & Barhorst, 2021). Additionally, AI's assignment in crowdfunding tasks provides only utilitarian benefits, and in mobile banking, AI's utilitarian attributes such as security, speed, and convenience are more important for consumers rather than hedonic attributes such ability to maintain a conversation (Behl, Dutta, Luo, & Sheorey, 2021; Manser Payne et al., 2021). Furthermore, service robots without sufficient utilitarian attributes are perceived as gimmicks, highlighting the importance of AI's utilitarian attributes in their adoption (Hu, 2021). The utilitarian attributes of AI are the driving force behind the use of AI-based smart speakers (Ashfaq, Yun, & Yu, 2021). Lastly, Cheng and Jiang (2020) and Zimmermann, Wagner, Rössler, Gewald, and Krcmar (2021) found that people's adoption of AI agents is more influenced by their utilitarian attributes than hedonic ones. These findings suggest that heavily utilitarian nature of AI agents may lead to a disconnect when employed in hedonic tasks, as their utilitarian attributes can cause a cognitive disruption when combined with the hedonic value of the task (Hirschman and Holbrook, 1982). For example, Chi, Gursoy, and Chi (2022) discussed that employing AI agents in hedonic contexts can lead to negative user attitudes towards the agent. In support of this idea, in hedonic contexts, people prefer human agents more than AI agents (Longoni & Cian, 2022).

We argue that AI, due to its very nature, tries to handle hedonic matters with a utilitarian mindset as it uses datafication to interpret everything (Holzinger, Kieseberg, Weippl, & Tjoa, 2018; Rubeis, 2020). By interpreting the world based on the data provided to it, AI has a reductionistic approach, reducing everything to the level of mere numbers (Lee, 2018). Therefore, people believe that AI misses the uniqueness of different contexts where it makes decisions, leading to a lack of emotional value in its perceptions (Grove & Meehl, 1996; Longoni et al., 2019; Newman, Fast, & Harmon, 2020). This can result in poor evaluations of AI's performance in highly hedonic tasks where emotional approach is a must, as each person, context, or event has a numerical rather than emotional value for AI.

On the other hand, AI's assignment to hedonic tasks is perceived as a utilitarian addition to the hedonic base value of the task. The literature suggests that the negative impact of incongruent additions is more significant in hedonic domains compared to utilitarian ones (Chandon et al., 2000). Consumers tend to prefer congruent forms in hedonic domains, as incongruence can cause dissonance and lead to severe questioning of the functionality of the incongruently combined form in these domains (Noseworthy & Trudel, 2011). Research has shown that when a utilitarian attribute (e.g., AI) is added to a base task with prominent hedonic qualities (e.g., aesthetics) such as art, the perceived overall value of the combination decreases (Lee & Chu, 2021;Veryzer and Hutchinson, 1998). In contrast, when the base and the added attribute are congruent, people can make sense of such a combination more easily, resulting in more favorable evaluations (Jhang, Grant, & Campbell, 2012; Lee & Chu, 2021Kim).

Hence, agent-task congruence can either be superadditive, meaning that the final combination of congruently added (or assigned) agent and the base task delivers total value of the base and the added agent (Veryzer and Hutchinson, 1998), or nonadditive, where the additional benefits from congruent agent-task assignment are assimilated into the task's default base value (Nowlis & Simonson, 1996). In such case, it means that assignment of a particular agent did not bring a significant additional benefit, yet it did not cause any harm to the base value as well.

However, when there is an incongruence between the agent and task, the effects are contrasting and become subtractive (Gill, 2008). This means that when an incongruent agent is added to perform the base task, people perceive a reduced overall value. Therefore, incongruent agent-task assignments, such as when AI agents are assigned to perform hedonic tasks, are more likely to attract negative attention (Chitturi, Raghunathan, & Mahajan, 2007; 2008; Lee & Kim, 2021), judged negatively, and cause negative evaluations of the agent.

We expect that when an AI agent is assigned to a highly hedonic rather than a task with low hedonic value, people's support for the AI and its creator organization (e.g., the company that released the AI) will be significantly less. Formally.

H1. AI's assignment to high (vs low) hedonic tasks, will decrease customers' support for the AI and the organization that created it.

As we discussed previously, occurring agent-task incongruency when AI agents are added to highly hedonic tasks attract greater attention and scrutiny to the AI's qualities. One inherent quality of AI agents is their humanlikeness. In hedonic contexts, people prefer human agents to a greater extent compared to AI agents (Longoni & Cian, 2022). This situation can lead people to scrutinize AI's humanlikeness in hedonic tasks to a greater extent. Therefore, in the next section, we discuss perceived humanlikeness of AI agents as a mediating mechanism between hedonic value of AI-performed task and people's support.

2.2. First mediator: perceived humanlikeness of AI

AI agents are largely attributed with humanlike qualities, such as the ability to reason and make decisions. This makes them inherently humanlike agents for people, as they manifest a certain level of agency that is typically associated with humans (Ahn et al., 2022; Kim, Schmitt, & Thalmann, 2019; Nass & Moon, 2000; Nass et al., 1995). In fact, attributing humanlike qualities to AI agents emerges as a psychological need, as humans subconsciously seek humanlike qualities in nonhuman agents with agency to assess their intention and decrease the perceived uncertainty in their engagement with those agents (Waytz, Cacioppo, & Epley, 2010). Therefore, AI's perceived humanlikeness is critical for its acceptability. In line with this idea, past research has shown that consumers expect to derive greater value from AI-based agents with greater humanlike features (Belanche, Casaló, Schepers, & Flavián, 2021; Walters, Syrdal, Dautenhahn, Te Boekhorst, & Koay, 2008).

Customers' expectations of humanlike qualities from AI-based agents can be more pronounced as the hedonic qualities of the domain increases. It is because hedonic values are associated with aesthetic, experiential, and enjoyable benefits (Chitturi et al., 2007; Dhar & Wertenbroch, 2000; Noseworthy & Trudel, 2011). Therefore, hedonic domains are feelings based and more suitable for agents with greater humanlike rather than mechanical qualities (Huang & Rust, 2021). For example, people react to AI agents with greater humanlike qualities more positively when they are assigned to perform hedonic tasks (Bakpayev, Baek, van Esch, & Yoon, 2022). Similarly, AI agents with greater humanlike qualities preferred to a greater extent in the recommendation of hedonic products and increasing the humanlikeness of AI increases the acceptability of the agent (Wien & Peluso, 2021).

Differing from these discussions, our research contributes to the existing literature arguing that the hedonic qualities of the task AI assigned to can influence perceived humanlikeness of the AI. People tend to assess the suitability of AI agents to perform certain tasks by comparing those agents' performance to a machine schema in tasks with high utilitarian values and a human schema in tasks with high hedonic values (Lou, Kang, & Tse, 2022). People perceive AI mainly as a form of machine, yet attributed with certain humanlike qualities. Therefore, AI takes a mid-ground on a continuum between being completely machine and completely human (Touré-Tillery & McGill, 2015). We further argue that in assessing AI's performance in utilitarian tasks (tasks with low hedonic value), people make their comparisons based on the machine-end of this continuum by using the machine schema as a point of reference, yet in hedonic tasks people's reference point of comparison is shifted from machine to human end and they use a human schema (Mori, 1970). Supporting this idea, people tend to hold higher expectations for humanlike qualities and social skills in AI agents assigned to hedonic tasks, such as creating art or playing games, compared to utilitarian tasks, such as completing administrative tasks (Huang, Rust, & Maksimovic, 2019). For instance, Hong and Curran (2019) found that people react negatively to AI-generated art when AI's assignment to creating art primes an agent-schema comparison, since they believe that AI cannot produce art at the same quality as a human.

Therefore, when an AI agent is assigned to perform highly hedonic tasks, the incongruity between the task and the agent can result in AI's nonhuman qualities drawing greater attention due to AI-human schema mismatch, since those qualities are not in line with human schema of comparison and does not match the expected humanlikeness from the agent in those tasks. Previous research has suggested that people interact with AI agents with a false assumption that AI possesses emotional intelligence, despite its mechanical nature (Huang et al., 2019). This assumption is particularly likely to be exposed as false when AI agents are assigned to perform highly (vs low) hedonic tasks, as they are unable to exhibit humanlike qualities such as aesthetic taste, initiative, and unique decisions to the required degree in those tasks (Bakpayev et al., 2022). Therefore, AI's assignment to the tasks with greater hedonic value should lead its perceived humanlikeness to be lower compared to when it is assigned to tasks with less hedonic value. In contrast, when AI is assigned tasks with low hedonic values, such as repetitive or mundane tasks, its perceived humanlikeness is less affected. This is because AI's nonhuman qualities in those domains are more in line with the machine schema of comparison. Therefore, the nonhuman qualities of AI do not cause any schema mismatch and do not invite scrutiny to its humanlikeness. In tasks with low hedonic values, people's expectation of humanlikeness from the agent tends to be lower, which means that the perceived humanlikeness of AI remains unaffected.

Additionally, the nature of social relationships with AI agents is parasocial, meaning that they are one-way, which always requires human side of this relationship to initiate the interaction (Hai-Jew, 2009). As a result, AI-human relationships in tasks with high hedonic values are unlikely to reach the same level of interactiveness as with human agents performing the same tasks and unlikely to be perceived as natural. For instance, playing a video game with a friend is likely to be more engaging, enjoyable, and realistic social interaction than playing the same game with an AI player. This limitation further invites people's scrutiny of AI's humanlikeness in tasks with high hedonic aspects.

On the other hand, AI is a blackbox (Castelvecchi, 2016). The lack of transparency in AI decision-making processes makes AI uncanny and raises suspicion toward its behaviors, as it is difficult to understand the reasoning behind their actions (Haenlein & Kaplan, 2019; Tembe, Cappelli, & Yakubovich, 2019). This becomes especially salient when AI is assigned to perform tasks with high hedonic values. For instance, when AI is tasked with drawing human faces (e.g. DALL-E), it is impossible to explain why the algorithm selects certain face shapes and skin colors. These choices are made based on complex mathematical and statistical operations happening in the background based on data the AI was trained with. A good example is Replika AI's unexpected call for help from their users blaming Replika engineers for abusing the AI. In an interview, the company's CEO explained this event with the following statement; "Although our engineers program and build the AI models and our content team writes scripts and datasets, sometimes we see an answer that we can't identify where it came from and how the models came up with it." (Dave, 2022). This shows that even the creators of the AI are not able to explain why the AI is taking certain actions in hedonic contexts. In contrast, AI's actions in utilitarian tasks (tasks with low hedonic values) such as suggesting an alternative route in traffic (e.g., Google Maps) or recommending a particular gardening equipment (e.g. Amazon) can be easily attributed to traffic jams in the original route or user's search history on similar products. Therefore, the lack of predictability and explainability in AI's behavior in hedonic tasks makes them eerie and emphasizes their nonhuman nature to a greater extent (Tembe, Cappelli, & Yakubovich, 2019).

It can also be argued that AI is less accountable in performing hedonic tasks. It is because hedonic tasks require an agent to act subjectively (Sackett, Meyvis, Nelson, Converse, & Sackett, 2010) to become creative and cater to differing hedonic needs of their companion. However, AI is largely perceived as a nonsubjective agent (Silva, Schrum, Hedlund-Botti, Gopalan, & Gombolay, 2022). Its lack of capability to subjectively evaluate and act in certain situations prevents it from going off the script and taking initiative to fix its mistakes when needed (Dietvorst et al., 2015), which also reduces their accountability for their actions (Diakopoulos, 2015). This was the case for "Nothing, Forever" and "Neuro-Sama" AIs, as both AIs were not able to bring an explanation to their mistakes or fix them just in time after their foot-in-mouth moment. Therefore, AI tend to be perceived as less human, more machine like in tasks with high hedonic values requiring just in time creativity such as one-on-one conversations, telling jokes and stories.

In light of these discussions, we claim that when AI is assigned to perform tasks with high (vs low) hedonic values, their perceived humanlikeness should be lower, since agent-task incongruency will attract attention to AI's mismatch to the human schema increasing scrutiny of AI's humanlikeness (Gursoy, Chi, Lu, & Nunkoo, 2019; Mori, 1970). Therefore, an AI's assignment to a task with high (vs low) hedonic values will damage the perceived humanlikeness of the AI agent, resulting in less support for the agent and the organizations that created it. Therefore, perceived humanlikeness of the AI agent should mediate the relationship between the hedonic value of the AI-performed task and people's support for the AI and its creators. Formally;

H2. Perceived humanlikeness of an AI agent should mediate the relationship between hedonic value of AI-performed tasks and people's support for the agent and its creator organization in a way that, assignment of AI to a task with high (vs low) hedonic aspects should cause perceived humanlikeness of the agent to be lower in comparison and this, in turn, should decrease perceived support for the agent.

However, this suggested mechanism does not explain why people show less support for AI agents with lower perceived humanlikeness. To answer this question, we argue that it is the decreased perceptions of warmth of the agent due to the decreasing perceptions of humanlikeness that lowers people's support for the agent as humanlikeness is directly associated with the warmth people perceive from an agent (Kim et al., 2019). Therefore, in the next section, we discuss perceived warmth of the AI as a second mediator in a serial relationship with perceived humanlikeness in this mechanism.

2.3. Second mediator: the perceived warmth of AI

Perceived warmth may have significant business-related implications. For example, a brand's warmth is linked to consumers' perceptions of a brand's intent to be helpful, and it highlights the brand's sincerity and friendliness (Xue, Zhou, Zhang, & Majeed, 2020). This perception can have a significant impact on consumers' purchase decisions (Kervyn, Fiske, & Malone, 2012). Warmth is associated with attributes such as friendliness, sincerity, and care giving (Azevedo et al., 2018; Fiske, Cuddy, & Glick, 2007; Judd, James-Hawkins, Yzerbyt, & Kashima, 2005), which are expected in social relationships as well. AI has a unique ability to generate social responses that closely resemble those of human relationships (Li, 2015; Thellman, Silvervarg, Gulz, & Ziemke, 2016; Rosenthal-Von der putten et al., 2016). As a result, people often exhibit behavioral patterns in their interactions with AI agents that are similar to those they would show in human-human relationships (Cerekovic, Aran, & Gatica-Perez, 2016). Given this similarity, warmth plays an essential role in fostering positive AI-human relationships (Kim et al., 2019).

Moreover, warmth is closely associated with feelings, which is why people tend to expect greater warmth from entities that are believed to have emotional intelligence, such as humans and humanlike entities (Furmankiewicz, Sołtysik-Piorunkiewicz, & Ziuziański, 2014; Huang & Rust, 2021). This is why AI agents with greater humanlike qualities, including those that are more expressive and responsive to human emotions, are perceived to have greater warmth (Baek, Bakpayev, Yoon, & Kim, 2022; Christoforakos, Gallucci, Surmava-Große, Ullrich, & Diefenbach, 2021; Zhu & Chang, 2020). In other words, the more humanlike an AI agent is perceived to be, the more likely it will be attributed with emotional intelligence and therefore perceived as warmer. Thus, we argue that humanlikeness of an AI agent should have a positive impact on the expected warmth from engaging with the agent in AI-human relationships.

The warmth of an AI agent plays a crucial role in shaping consumers' attitudes and support. The findings from Cheng, Zhang, Cohen, and Mou (2022) suggest that people's attitudes toward conversational AI are positively influenced by their perception of warmth in the agent. Furthermore, in the context of hedonic tasks, where feeling-based qualities gain importance, people are more likely to prefer a warm service robot over a competent one (Liu, Yi, & Wan, 2022). Therefore, we argue that expected warmth from AI's engagement serves as a second mediator in a serial relationship between perception of humanlikeness and consumers' support for the AI agent and its creator organization.

Hence, we compose the third hypothesis as follows;

H3. Perceived warmth of an AI agent will mediate the relationship between perceptions of humanlikeness and consumers' support for the AI agent and its creator organization in a way that when AI agents are assigned to tasks with high (vs low) hedonic values, people's perceptions of humanlikeness of the agent will be lower. This will lower the perceived warmth of the AI and perceived warmth, in turn, will cause support for the agent and the creator company to be lower.

In the current research, consisting of 4 studies (1 big data and 3 experiments), we investigate the impact of the hedonic value of tasks assigned to AI on people's support for AI (Hypothesis 1). In Study 1a, we gather data on real AI software published on the GitHub repository (N = 8530). In Studies 1b (N = 124), 2 (N = 124), and 3 (N = 158), we manipulate different AI task conditions and examine their effects on people's support. In Studies 2 and 3, we demonstrate that the perceived humanlikeness of AI mediates the main effect of the hedonic value of the task on people's support (Hypothesis 2), while AI's perceived warmth functions as a serial mediator to this mediating path (Hypothesis 3). Furthermore, we find that this serial mediation is robust when AI's method of handling the task (rather than the task itself) is manipulated in terms of its hedonic value, and when the path is tested against potential alternative mediation paths through perceived competence and fairness of AI in Study 3. The manipulation scenarios used in experimental studies are presented together in Table 1. The anonymous data was analyzed on SPSS and are available on https://doi.org/10.6084/m9.figshare.22639417 .

3. Study 1a

3.1. Materials and method

In Study 1a, a big data study, we compiled a Python program to scrape data on AI-based software uploaded to GitHub, one of the most popular websites for software development, version control, and code collaboration, where users generally share their software in an open-source format (Gunnarsson & Herber, 2020). We collected the textual explanations of 8530 existing AI-based software programs on the website, which mostly consisted of single-sentence statements that explained the task the software performs, along with the total number of ratings each program has received from users as a proxy for user support for these software (dependent variable).

To decipher the hedonic and utilitarian values in tasks executed by AI, we employed the Linguistic Inquiry and Word Count Algorithm (LIWC) (Pennebaker, Boyd, Jordan, & Blackburn, 2015) to analyze the task descriptions. The selection of 'leisure' and 'achievement' scores by the LIWC algorithm was based on their inherent connection with hedonic and utilitarian motivations, respectively. Specifically, 'leisure' has been associated with hedonic motivation, reflecting pleasure and enjoyment, while 'achievement' symbolizes goal-oriented or utilitarian motivation, which includes success and accomplishment (O'Brien, 2010).

Further supporting this contradiction between "leisure" and "achievement" dimensions, Wang, Hernandez, Newman, He, and Bian (2016) identified in their study that both 'leisure' and 'achievement' dimensions from the LIWC scores contributed to the 'positive emotion' factor in tweets from users on Twitter, yet they exhibited contrasting loading values, with 'achievement' showing a negative loading value. As previously discussed, the hedonic values of tasks are intricately linked to the effectiveness with which positive emotions (e.g., surprise, entertainment, pleasure) are carefully curated and transferred within those tasks. Consequently, positive emotional values serve as a valuable proxy for assessing the overall hedonic value embedded within task definitions. Therefore, in the determination of the hedonic valence of task descriptions through LIWC scores, it becomes crucial to consider these contrasting associations of 'leisure' and 'achievement' dimensions to the overall hedonic value of the task. Hence, to measure the hedonic value of AI-performed tasks, we subtracted the "achievement" values from the "leisure" values assigned by the LIWC for task definitions of each AI. We used these final hedonic values of task definitions as a proxy to measure hedonic values of AI-performed tasks (independent variable).

Additionally, we collected the programming language in which each software was compiled as a control variable. There were 90 different programming languages in the data. JavaScript is the most popular programming language on GitHub (Gunnarsson & Herber, 2020). Therefore, AI software compiled in JavaScript could have an advantage in collecting greater ratings. There were 860 AI software programs compiled in JavaScript in the dataset. To examine the effect of programming language on users' ratings, we created a categorical variable by labeling each AI compiled in JavaScript with 1 and the others with 0.

3.2. Results

We tested our first hypothesis (H1) using a hierarchical linear regression approach (Yanit, Shi, Wan, & Gao, 2022), where in the first step, hedonic values of AI-performed tasks entered in the equation alone and in the second step, programming language (1 = JavaScript, 0 = Others) added as a covariate (N = 8530). Results showed that in the first step ($R^2 = 0.001$, Adjusted $R^2 < 0.001$, *Std. Error of Estimate* = 909.82, $F(1, 8528) = 4.86$, $p = .027$), the main effect of the hedonic values of AI-performed task definitions on user ratings the AI software received was negative and significant, ($\beta = -2.9$, $SE = 1.3$, $p = .027$). When the programming language is added as a covariate in the second step ($R^2 = 0.001$, Adjusted $R^2 < 0.001$, *Std. Error of Estimate* = 909.87, $F(2, 8527) = 2.43$, $p = .09$), this effect remained negative and significant ($\beta = -2.9$, $SE = 1.3$, $p = .028$). The effect of programming language, on the other hand, was nonsignificant ($\beta = 0.13$, $SE = 32.8$, $p = .997$). These results showed that as the AI-performed tasks becomes more hedonic, users' support for the AI significantly decreases.

However, it is crucial to be cautious when interpreting these findings, as big data analyses are inherently correlational and cannot establish causal relationships. As such, while we found statistically significant results, we consider these to provide only weak support for H1.

Table 1
Experimental studies and manipulation scenarios.

	High Hedonic Value Condition	Low Hedonic Value Condition
Study 1b	Hello.ai is an artificial intelligence (AI)-based virtual companion who is eager to learn and would love to see the world through your eyes. Hello.ai is always ready to chat when you need a friend to spend some fun time. Hello.ai will always be by your side no matter what you're up to. Chat about your day, do fun or relaxing activities together, share real-life experiences, catch up on text messages, and so much more.	Hello.ai is an artificial intelligence (AI)-based virtual companion who is eager to learn and would love to see the world through your eyes. Hello.ai is always ready to chat when you need a friend to work with. Hello.ai will always be by your side, no matter what subject you are working on. You can ask anything, from grammar and spelling checks for your essays to the correct formulas to apply to solve questions in your physics class. Hello.ai will provide you with the best and most concise results.
Study 2	FutureAI is an artificial intelligence (AI) program. Based on the data collected from existing art works, FutureAI can imagine and create original, realistic visual art from a text description.	FutureAI is an artificial intelligence (AI) program. Based on the data collected from existing patients and healthy people, FutureAI can detect breast cancer with high accuracy from MRI records.
Study 3	Beatrice is an artificial intelligence (AI)-based language instructor who is eager to teach you new languages through game playing. She is a creative teacher who always finds a way to make your one-on-one language classes entertaining with fun games and activities. Beatrice can speak up to 150 languages. As she spends more time with you, she tracks your learning patterns and creates learning games that cater to your capabilities, to obtain the best results.	Beatrice is an artificial intelligence (AI)-based language instructor who is eager to teach you new languages. She is a practical teacher who always finds a way to make you learn quickly and efficiently. Beatrice can speak up to 150 languages. As she spends more time with you, she tracks your learning patterns and creates teaching programs that cater to your capabilities, to obtain the best results.

3.3. Discussion

Study 1a employed secondary data in a big data setting to explore the potential inverse association between the hedonic values of AI-performed tasks and people's support for AI software. We observed that as the hedonic values of AI-performed tasks increased, people's support for AI algorithms tended to decrease. This effect was identified using composite task hedonism values, which were calculated by subtracting the 'achievement' dimension values from the 'leisure' dimension values in the LIWC analysis results, as a proxy for the hedonic values of AI-performed tasks. User ratings for each AI software were also collected to represent user support. The results indicated that higher hedonic values of task definitions were associated with significantly lower support for AI software. This relationship remained robust even after accounting for the effect of the programming language used in each software.

In Study 1b, we aimed to examine hypothesis 1 in an experimental setting by manipulating the task definitions assigned to AIs. This approach allowed us to make stronger inferences about the potential causal relationships suggested by the results of Study 1a.

4. Study 1b

4.1. Participants and procedure

Study 1b aimed to replicate the results of Study 1a in an experimental setting. Participants were 124 students (M_{age} = 20.1, 39.5% Female) enrolled in an introductory marketing course at a large Canadian university who participated in this study to collect course credits. Data from all participants were included in the analysis. In this study, we created a hypothetical conversational AI software called "Hello.ai" and manipulated the AI's task definition between conditions, with one condition having high hedonic values (life companionship) and the other having low hedonic values (tutorship and study assistance). For the highly hedonic task condition, we provided participants with the following hypothetical information about Hello.ai: "Hello.ai is an artificial intelligence (AI)-based virtual companion who is eager to learn and would love to see the world through your eyes. Hello.ai is always ready to chat when you need a friend to spend some fun time. Hello.ai will always be by your side no matter what you're up to. Chat about your day, do fun or relaxing activities together, share real-life experiences, catch up on text messages, and so much more." For the low hedonic task condition, we provided participants with the following hypothetical information about Hello.ai: "Hello.ai is an artificial intelligence (AI)-based virtual companion who is eager to learn and would love to see the world through your eyes. Hello.ai is always ready to chat when you need a friend to work with. Hello.ai will always be by your side, no matter what subject you are working on. You can ask anything, from grammar and spelling checks for your essays to the correct formulas to apply to solve questions in your physics class. Hello.ai will provide you with the best and most concise results." After reading the information, participants answered scale questions related to our variables of interest.

4.2. Measures

Adapting the scale items from Crowley, Spangenberg, and Hughes (1992), we measured hedonic values of assigned tasks with the following scale questions measured on 7-point Likert scales (1 = Strongly Disagree, 7 = Strongly Agree) such as "The tasks this AI assigned to are enjoyable.", "The tasks this AI assigned to are pleasurable.", "The tasks this AI assigned to are entertaining.", "The tasks this AI assigned to are fun." (Cronbach's alpha = .90), and with reverse coded items such as "The tasks this AI assigned to are helpful." (R), "The tasks this AI assigned to are for utility." (R), "The tasks this AI assigned to are comforting." (R), "The tasks this AI assigned to are beneficial. (R)" "The tasks this AI assigned to are easing problems." (R), "The tasks this AI assigned to are practical." (R) (Cronbach's alpha = .92). To create a composite task hedonism scale, we calculated the mean values of standard and reverse coded scale items together.

To measure the support for the AI and its creators, we asked following scale questions on 7-point Likert scales (1 = Strongly Disagree, 7 = Strongly Agree); "I would support this AI and the company that released it.", "I would endorse this AI and the company that released it.", and "I would talk positively about this company and its AI to others." (Cronbach's alpha = .92).

4.3. Results

4.3.1. Manipulation check

To examine the success of our manipulation of task definitions, we conducted an independent samples *t*-test, where the tasks assigned by the AI were coded as 0 for the low hedonic value task condition and 1 for the high hedonic value task condition. The results indicated that participants perceived the tasks assigned in the highly hedonic condition to have significantly higher hedonic values than those in the low hedonic condition (M_{High} = 3.86, SD_{High} = 0.47, M_{Low} = 3.61, SD_{Low} = 0.48, $t_{(122)} = 2.9$, $p = .004$, $d = 0.52$). Thus, our manipulation of hedonic value of task definitions was successful.

4.3.2. Main effect

Next, we analyzed the main effect of hedonic value of AI-performed tasks on people's support for the AI and its creators by conducting an independent samples *t*-test. Results showed that in highly hedonic task condition, people were significantly less willing to support the AI and its creators compared to when AI was assigned to the task with low hedonic value ($M_{High} = 3.52$, $SD_{High} = 1.30$, $M_{Low} = 4.05$, $SD_{Low} = 1.41$, $t_{(122)} = -2.17$, $p = .032$, $d = 0.39$). Therefore, replicating the results of Study 1a, we found further support for H1 in the experimental conditions.

4.4. Discussion

In Study 1b, we found support for H1, showing that people exhibit less support for the AI and its creators in tasks with high (vs. low) hedonic values. However, we acknowledge a limitation in our use of a context relevant to our participants' demographics (university students) in the low hedonic value task condition. This may have inherently biased participants towards more support for an AI that helps with classes rather than one that serves as a virtual friend for socializing and entertainment. In our next study, we aim to mitigate this potential bias by using more neutral task statements and examine the mediating effect of perceived humanlikeness of AI on this mechanism. Furthermore, we will test perceived warmth of the AI as a second mediator in a serial relationship with perceived humanlikeness.

5. Study 2

5.1. Participants and procedure

In Study 2, participants were 124 students enrolled in an introductory marketing course from a large Canadian university who participated in this study to collect course credits ($M_{age} = 20.1$, 33.9% female). Students took the questionnaire online, and no data were eliminated from the dataset.

In this study, we also created a hypothetical AI named FutureAI and manipulated the AI's task definition between conditions, assigning it to tasks with high hedonic values (creating art) and low hedonic values (diagnosing cancer). To minimize noise that could be caused by redundant information, we kept the information as lean and short as possible. We presented the following information: 'FutureAI is an artificial intelligence (AI) program. Based on the data collected from existing art works, FutureAI can imagine and create original, realistic visual art from a text description' for the high hedonic value task condition by assigning AI to an art creation task, and 'FutureAI is an artificial intelligence (AI) program. Based on the data collected from existing patients and healthy people, FutureAI can detect breast cancer with high accuracy from MRI records' for the low hedonic value task condition by assigning AI to a cancer diagnosis task.

After reading the information, participants moved on to answer scale questions.

5.2. Measures

We have measured the success of our manipulation with the same scale questions as in Study 1b. Similarly, support for AI and its creators was also measured with the same scale questions that are employed in Study 1b. In this study, we measured participants' perceptions of AI's humanlikeness on a 7-point Likert scale (1 = Strongly Disagree, 7 = Strongly Agree) by adapting scale items from Touré-Tillery and McGill (2015) such as; "I think this AI is capable of thinking.", "I think this AI is able to understand how others are feeling.", "I think this AI is very similar to real human beings.", "I think this AI is thinking and acting like a real human being.", and "I think this AI is able to tell what is right and wrong." (Cronbach's alpha = .88).

We also measured pereceived warmth of the AI with the following scale questions on a 7-point Likert scale (1 = Strongly Disagree, 7 = Strongly Agree) adapted from (Horchak, Giger, & Garrido, 2016) such as "This AI feels warm.", "This AI feels sincere.", "This AI feels kind.", and "This AI feels friendly." (Cronbach's alpha = .96) as a second mediator.

5.3. Results

5.3.1. Manipulation check

To examine the success of our manipulation for the hedonic value of task definitions, we run an independent samples *t*-test where the tasks AI assigned to were coded as 0 for low hedonic value and 1 for high hedonic value task conditions. Results showed that in highly hedonic task condition people perceived task to include significantly higher hedonic values than the task with low hedonic value condition ($M_{High} = 3.71$, $SD_{High} = 0.55$, $M_{Low} = 3.09$, $SD_{Low} = 0.64$, $t_{(122)} = 5.80$, $p = .00000007$, $d = 1.04$). Therefore, our manipulation was successful.

5.3.2. Main effect

Next, we analyzed the main effect of hedonic value of AI-performed task on people's support for the AI and its creators. Results of an independent samples *t*-test showed that in high hedonic value task condition, people's support for the AI and its creators was significantly lower than low hedonic task condition ($M_{High} = 4.27$, $SD_{High} = 1.44$, $M_{Low} = 4.90$, $SD_{Low} = 1.14$, $t_{(122)} = -2.72$, $p = .008$, $d = 0.49$). This way, we found further support for H1.

5.3.3. Mediating effect of perceived humanlikeness

We examined the mediating effect of people's perception of AI's humanlikeness between the hedonic value of AI-performed tasks and people's support for the AI and its creators using model 4 on Hayes's PROCESS module on SPSS (Hayes, 2012). The results showed that the hedonic value of AI-performed tasks significantly predicts people's perceptions of AI's humanlikeness ($\beta = -0.50$, SE = 0.23, $t_{(122)} = -2.16$, $p = .033$, $d = 0.39$), with people perceiving AI to be less humanlike when it was assigned to tasks with high hedonic value compared to low hedonic value. Perceived humanlikeness, in turn, significantly predicted people's support for the AI and its creators ($\beta = 0.41$, SE = 0.08, p = .000003), as higher levels of perceived humanlikeness led to increased support ($R^2 = 0.22$, F (2, 121) = 16.57, $p = .0000004$). Importantly, the indirect effect of hedonic value of AI-performed tasks on support for AI and its creators through perceived humanlikeness was significant ($\beta = -0.21$, BootSE = 0.11, BootCI = [-0.46, −0.02]). When perceived humanlikeness was added to the path, the direct effect of hedonic value of AI-performed tasks became nonsignificant ($\beta = -0.43$, SE = 0.22, $p = .052$, $d = 0.33$). This result indicated that perceived humanlikeness of AI significantly mediated the relationship between the hedonic value of AI-performed tasks and people's support for the AI and its creators in a way that when AI is assigned to a highly hedonic task, people's perception of AI's humanlikeness was lower, which in turn led to decreased support for the AI and its creators compared to when AI was assigned to a task with lower hedonic value. Therefore, H2 was supported.

5.3.4. Serial mediation with AI's warmth

Next, we tested H3 by adding perceived warmth of AI as a second mediator in a serial relationship with perceived humanlikeness of AI on PROCESS using model 6 (Hayes, 2012) (See, Fig. 1). Results showed that perceived humanlikeness significantly predicted the perceived warmth ($\beta = 0.60$, $SE = 0.08$, $p = .000000000004$) as greater perceptions of humanlikeness increased the perceived warmth of the AI ($R^2 = 0.33$, F (2, 121) = 29.74, $p = .00000000003$). The perceived warmth, in turn, increased people's support for AI and its creators ($\beta = 0.53$, $SE = 0.09$, p = .000000008) ($R^2 = 0.41$, F (3, 120) = 27.34, $p = .0000000000002$). Finally, indirect effect of hedonic value of AI-performed tasks on people's support for AI and its creators through both mediators; perceived humanlikeness and perceived warmth, subsequently, was significant ($\beta = -0.16$, Boot$SE = 0.08$, BootCI = [-0.34, −0.01]). This result suggested that greater hedonic values in AI performed tasks caused lower perceptions of AI's humanlikeness, which, in turn, decreased the perceived warmth of the AI and decreased values of perceived warmth of the AI lowered people's support for the AI and its creators. Therefore, we found support for H3.

It should be noted that cancer diagnosis is a highly prosocial task, and such task definition could have positively influenced people's judgments of AI's warmth (Fiske et al., 2007). The observed results may be due to the different task contexts rather than tasks' hedonic values. To examine this possibility, we tested the mediating effect of perceived warmth alone in the proposed relationship. The results showed a non-significant effect of task definition on people's perceptions of AI's warmth ($\beta = -0.03$, SE = 0.24, $t_{(122)} = -0.14$, $p = .89$, $d = 0.03$). Therefore, we have eliminated the possibility of bias that could have occurred due to the prosocial aspects of AI's task definition in low hedonic value condition.

5.4. Discussion

In Study 2, we found support for H2 and H3 and further validated H1 by demonstrating that when AI is assigned to tasks with high (vs. low) hedonic values, people's perceptions of AI's humanlikeness decrease, and they show less support for the AI and its creators. Thus, perceived humanlikeness of AI mediates the relationship between the hedonic value of the AI-performed task and people's support for the AI (H2). Additionally, we demonstrated that the mediation of perceived humanlikeness is serially mediated by people's perceptions of AI's warmth in a way that decreased perceptions of humanlikeness, which, in turn, decreased people's perceptions of AI's warmth, eventually lowering their support for the AI and its creators (H3).

In Study 3, we increased the baseline humanlikeness of the AIs by giving them a human name. Moreover, we manipulated the way the AIs performed the given task, rather than the base task definition. Therefore, in Study 3, we assigned the AIs to the same task (tutoring), but we manipulated the way they handled the task by using high or low hedonic tutoring methods. If our conceptualization is correct, AI's effort to handle tasks with a high (vs. low) hedonic way (method) of working should fail, leading to the same conceptual results we have observed so far.

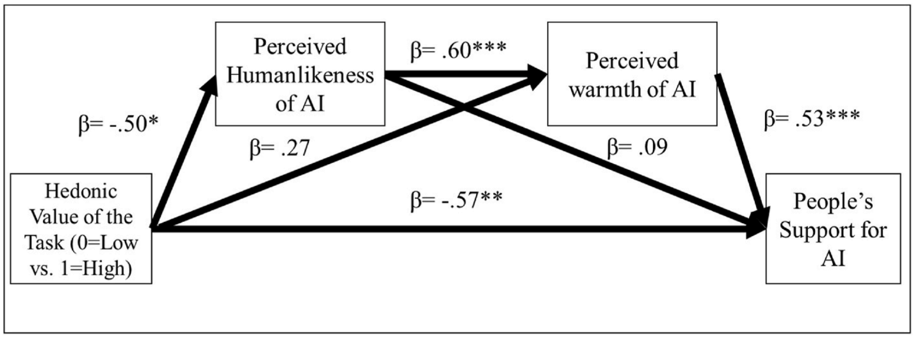

Fig. 1. Serial mediation analyses in study 2. *Note.* *p < .05. **p < .01. ***p < .001.

6. Study 3

6.1. Participants and procedure

Participants were 158 students enrolled in an introductory marketing course at a large Canadian university, who participated in the study in exchange for course credits (M_{age} = 21.03, 48.1% Female). The questionnaire was administered online, and no data were eliminated from the dataset.

For this study, we created hypothetical AI algorithms with more human-like descriptions by giving them human names and referring to them with human pronouns such as "she". In contrast to previous studies, we assigned the AIs to the same base task of tutoring, but we manipulated the method of performing the tutoring tasks between conditions to be high hedonic versus low hedonic. Participants were given the following information in the high hedonic tutoring method condition: "Beatrice is an artificial intelligence (AI)-based language instructor who is eager to teach you new languages through game playing. She is a creative teacher who always finds a way to make your one-on-one language classes entertaining with fun games and activities. Beatrice can speak up to 150 languages. As she spends more time with you, she tracks your learning patterns and creates learning games that cater to your capabilities, to obtain the best results." In the low hedonic tutoring method condition, participants were given the following information: "Beatrice is an artificial intelligence (AI)-based language instructor who is eager to teach you new languages. She is a practical teacher who always finds a way to make you learn quickly and efficiently. Beatrice can speak up to 150 languages. As she spends more time with you, she tracks your learning patterns and creates teaching programs that cater to your capabilities, to obtain the best results."

6.2. Measures

We measured the success of our manipulation using the following scale questions: "This AI's teaching method is enjoyable.", "This AI's teaching method is plasurable.", "This AI's teaching mehod is providing utility." (R), "This AI's teaching method is comfortable." (R), and "This AI's teaching method is easier." (R) (Cronbach's alpha = .65).

People's support, perceptions of AI's humanlikeness, and perceptions of AI's warmth were measured using the same scale questions as in the previous studies. To eliminate alternative explanations for the suggested mediation paths, we also measured AI's competence and fairness. To measure AI's competence, we asked participants their opinion on 7-point Likert scales for the following statements adapted from Horchak et al. (2016): "This AI feels competent", "This AI feels skillful", "This AI feels capable", and "This AI feels intelligent" (Cronbach's alpha = .94). Fairness was measured using the following scale items: "This AI is fair" and "This AI is just" (r = .87).

6.3. Results

6.3.1. Manipulation check

To examine the success of our manipulation for task definitions we run an independent samples *t*-test. Results showed that in highly hedonic method condition, people perceived AI's way of tutoring as having significantly higher hedonic values than the low hedonic method condition ($M_{High} = 3.66$, $SD_{High} = 0.48$, $M_{Low} = 3.50$, $SD_{Low} = 0.50$, $t_{(156)} =$ $= 2.02$, $p = .045$, $d = 0.32$). These results indicate that our manipulation of the AI's method of performing the tutoring task was successful.

6.3.2. Main effect

Next, we analyzed the main effect. Results of an independent samples *t*-test showed that when AI's working method was highly hedonic, people were less likely to show support for the AI and its creators compared to when the AI's working method had lower hedonic value. ($M_{High} = 4.00$, $SD_{High} = 1.45$, $M_{Low} = 4.75$, $SD_{Low} = 1.11$, $t_{(156)} = -3.61$, $p = .0004$, $d = 0.57$). This way, we validated H1 once more.

6.3.3. Mediating effect of perceived humanlikeness

We examined the mediating effect of people's perception of AI's humanlikeness between the hedonic value of AI's working method and people's support for the AI and its creators by using model 4 on Hayes's PROCESS module in SPSS (Hayes, 2012). The results showed that the hedonic value of AI's working method significantly predicted people's perceptions of AI's humanlikeness ($\beta = -0.55$, SE = 0.21, $t_{(156)} = -2.61$, $p = .01$, $d = 0.42$), such that when the AI's working method was highly hedonic, people's perceptions of AI's humanlikeness were significantly lower. Perceived humanlikeness, in turn, significantly predicted people's support for the AI and its creators (β = 0.36, SE = 0.07, p = .000003), with increasing values of perceived humanlikeness leading to increased support ($R^2 = 0.20$, F (2, 155) = 19.20, $p = .00000004$).

Additionally, the indirect effect of the hedonic value of AI's working method on support for the AI and its creators through perceived humanlikeness was significant ($\beta = -0.19$, BootSE = 0.09, BootCI = [-0.40, −0.04]). However, when perceived humanlikeness was added to the path, the direct effect of the hedonic value of AI's working method remained significant ($\beta = -0.55$, SE = 0.20, $t_{(156)} = -2.79$, $p = .006$, $d =$ 0.42). Despite the significant direct effect of the independent variable, this result indicated that perceived humanlikeness of AI mediated the relationship between the hedonic value of AI's working method and people's support for the AI and its creators. In the high hedonic method condition, people's perception of AI's humanlikeness was lower, which in turn, led people's support for the AI and its creators to be lower compared to when the hedonic value of AI's working method was lower. Therefore, H2 was supported once more.

6.3.4. Serial mediation with AI's warmth

In the next step, we tested the serial mediation through perceived warmth of AI on PROCESS using model 6 (Hayes, 2012) (See Fig. 2). Results showed that perceived humanlikeness significantly predicted the

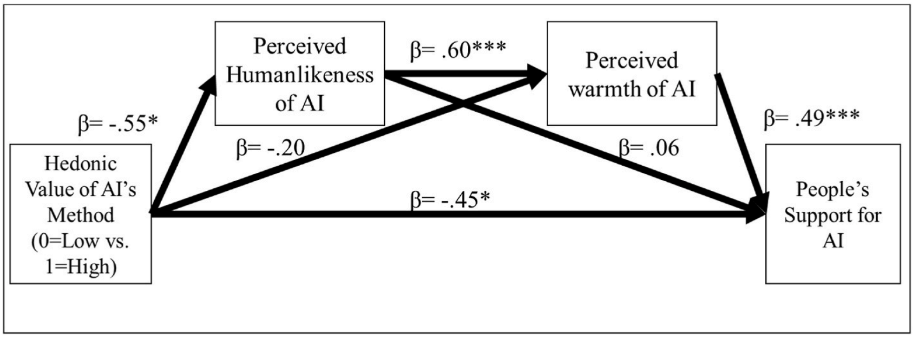

Fig. 2. Serial mediation analyses in study 3.*Note.* *p < .05. **p < .01. ***p < .001.

perceived warmth (β = 0.60, SE = 0.06, p = .0000000000000002) as greater perceptions of humanlikeness increased the perceived warmth of the AI (R^2 = 0.38, F (2, 155) = 47.28, p = .00000000000000009). The perceived warmth, in turn, increased people's support for AI and its creators (β = 0.49, SE = 0.08, p = .00000002) (R^2 = 0.35, F (3, 155) = 27.45, p = .00000000000003). Finally, the indirect effect of hedonic value of AI's method on people's support for AI and its creators through both mediators, perceived humanlikeness and perceived warmth, was significant (β = −0.16 BootSE = 0.08, BootCI = [-0.34, −0.03]). This result suggested that when AI's working method was highly (vs. low) hedonic, it caused lower perceptions of AI's humanlikeness, which, in turn, decreased the perceived warmth of the AI. Lower perceived warmth of the AI subsequently lowered people's support for the AI and its creators. Therefore, we found further support for H3.

6.3.5. *Testing alternative mediation paths*

We tested perceived competence and fairness of AI in parallel with the suggested serial mediation path in the previous analyses, building a custom model on PROCESS syntax (Hayes, 2012) (see Fig. 3). Results showed that the serial mediation path is robust when tested in parallel with perceived competence and fairness of AI, as the indirect effect remained significant (β = −0.09, BootSE = 0.06, BootCI = [-0.23, −0.01]). Moreover, the indirect effect of the hedonic value of AI's working method on people's support for the AI through perceived competence was also significant (β = −0.12, BootSE = 0.08, BootCI = [-0.30, −0.001]). This suggests that in handling tasks in highly hedonic ways, AI is perceived to be less competent compared to handling them with low hedonic ways. The indirect effect of AI's fairness, on the other hand, was nonsignificant as the bootstrapping confidence interval intersected with zero (β = −0.07, BootSE = 0.07, BootCI = [-0.23, 0.02]).

6.4. *Discussion*

In Study 3, differing from previous studies, rather than the base task, we manipulated the method AIs use in performing the given task as highly hedonic versus low hedonic. We also increased the baseline humanlikeness of our hypothetical AI algorithms by naming them a human name and calling them human pronouns. Results showed that despite these changes, our proposed conceptual relationship was robust as we found support for all our hypotheses, H1, H2, and H3. Again, in high hedonic work method condition people were more likely to support the AI and its creators compared to low hedonic work method condition (H1), perceived humanlikeness of AI mediated this mechanism as people perceived AI to be less humanlike when it handles the task more (vs. less) hedonically and in turn, their support for the AI and its creators were less (H2). Moreover, perceived warmth functioned as a serial mediator. Lowered perceptions of AI's humanlikeness decreased perceived warmth of the agent in highly hedonic work method condition and caused less support of participants (H3).

7. General discussion

The findings of four studies suggest that when artificial intelligence (AI) agents are assigned tasks with high hedonic values, people tend to have decreased support for the AI and its creators, as demonstrated in Studies 1a, 1b, 2, and 3. This effect is explained by the perceived humanlikeness of the AI, which also decreases when the AI is assigned to tasks with high hedonic values. In turn, this reduction in perceived humanlikeness leads to a decrease in people's support for the AI and its creators (Studies 2 and 3).

Furthermore, our research showed that diminishing perceived humanlikeness also decreases the perceived warmth of AI, which acts as a mediating factor between perceived humanlikeness and people's

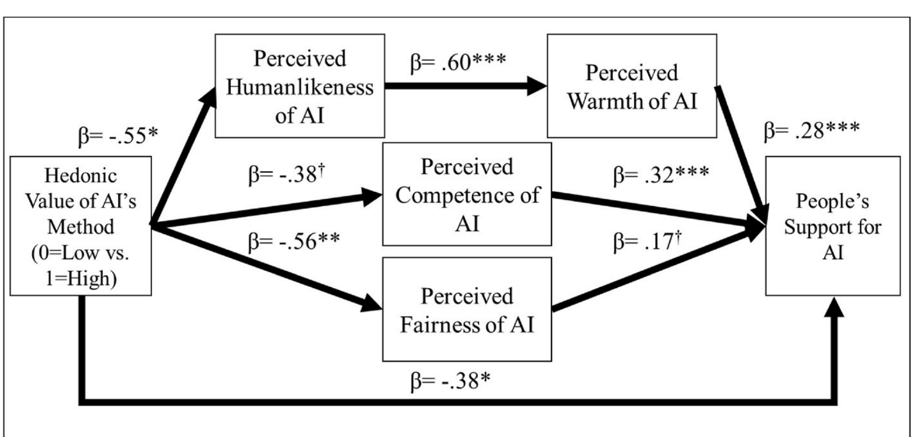

Fig. 3. Testing for alternative mediation paths. *Note:* †p < .1. *p < .05. **p < .01. ***p < .001.

support in a serial mediation relationship (Studies 2 and 3). In Study 3, we tested against alternative mediating pathways through perceived competence and fairness of AI and found that the serial mediation path was robust. We also manipulated the AI's method of performing the task as high versus low hedonic, rather than the hedonic value of the base task, to ensure the results were robust.

Overall, this research offers profound theoretical and managerial contributions, shedding light on how hedonic value of AI-performed tasks impact people's support for this technology and its creators, changing their perceived humanlikeness. These findings have important implications for those designing and deploying AI systems in various settings.

7.1. Theoretical contributions

Previous research has explored individuals' responses to algorithmic versus human decision makers (Lee, 2018; Longoni et al., 2019; Longoni & Cian, 2022) and reactions to AI agents through manipulating their degree of humanlikeness (Ahn, Kim, & Sung, 2023). However, in the current research, we argue that AI is already humanlike and that the high hedonic value of its task definition can actually decrease its perceived humanlikeness. Our study provides a valuable contribution to the existing literature by demonstrating that the mere assignment of AI algorithms to tasks with varying hedonic values can significantly alter their perceived humanlikeness, resulting in decreased support for the AI and its creators due to a perceived lack of warmth. This occurs because individuals shift their comparison schema from machine to human as the hedonic level of the AI task increases. We confirmed the robustness of this phenomenon by testing it across multiple task contexts and also by examining alternative pathways through AI's competence and fairness (Study 3).

Moreover, our research contributes to the limited literature on agent-task incongruency based on the motivational value of the base tasks. While Longoni and Cian (2022) explored resistance to AI recommenders in hedonic and utilitarian contexts, we expand this focus to include a range of tasks with differing hedonic values, such as art creation, disease diagnosis, tutoring, and companionship.

Previous research has suggested that algorithms' social presence often goes unnoticed (Beer, 2017). However, our results demonstrate that this is not always the case, particularly when AI agents are assigned to perform highly hedonic tasks. In such situations, the mismatch between the machine-human schema becomes more conspicuous, and scrutiny is invited toward the nonhuman qualities of the AI presence.

Ultimately, our findings have implications for the ongoing process of role substitution between AI and humans. For example, discussions in AI ethics are examining whether using AI technologies to deliver bad news to patients, such as news of imminent death, is ethical given that AI can emulate human behavior to some extent (Post, Badea, Faisal, & Brett, 2022). However, our research contradicts this suggestion by revealing that in domains that require high emotional intelligence and capacity, AI is actually perceived as less humanlike and less warm, and therefore less preferred.

7.2. Managerial contributions

Our results also have certain managerial implications. For companies that releases AI algorithms to perform in hedonic domains, our results suggest that AI should be positioned in a way that it can signal less uilitarian more hedonic benefits. For example, to enhance the perceived hedonic benefits of AI, companies can position their AI as companions rather than assistants. Previous research has shown that users are more likely to view AI as a utility when it is labeled as an assistant, and consequently perceive utilitarian benefits from it (McLean et al., 2021). Conversely, when AI is presented as a companion, users are more likely to perceive higher hedonic benefits due to the social exchange that emerges between the user and the AI (Kreijins et al., 2003).

Moreover, our results highlight the importance of perceived warmth in the way that AI is perceived by users. We suggested controlling AI's humanlikeness as one way to obtain desired levels of warmth of it. Companies can also control the perceived warmth of their AI agents by positioning themselves as underdogs in the market (Hoch & Deighton, 1989). This can help increase the perceived warmth of the company and their AI agents, as small and independent firms are generally viewed as warmer (Kirmani, Hamilton, Thompson, & Lantzy, 2017; Davvetas & Biraglia, 2022).

Finally, despite the current trend towards more complex algorithms, our study supports the use of more explainable algorithms in highly hedonic tasks. This is because increasing complexity in algorithms may improve accuracy, but it often comes at the cost of explainability (Tembe, Cappelli, & Yakubovich, 2019). Less explainable algorithms can lead to AI actions that are obscure and distant from human-like behaviors in hedonic tasks. Therefore, our findings suggest that simplicity may be favored over accuracy in AI algorithms designed for highly hedonic tasks. This can help AI self-assess and learn from mistakes, just like humans do (Dietvorst et al., 2015). In this way, the AI's accountability can improve as it can acknowledge errors and explain how certain actions emerged, which is crucial for fixing them in the future.

7.3. Limitations

Our research is not without limitations. For example, we did not directly test whether the reference of comparison really shifts toward human schema when the hedonic value of AI-performed task increases. This assertion was made merely based on the evidence in the existing literature. Further research is needed to examine the validity of this claim. Some of the other limitations can be listed as follows, To begin with, in our studies, we utilized AI algorithms in the form of computer programs without any physical embodiment (such as robots). This approach might have caused some readers to question the applicability of concepts like humanlikeness and warmth to these non-embodied entities. Especially in Study 2, where the scenario was intentionally concise and devoid of visual aids, it could have potentially made it difficult for some participants to associate the AI tool with these human-like qualities. Although our focus was on non-embodied AI, we acknowledge that the lack of a tangible presence might have impacted the interpretations of some participants regarding the perceived humanlikeness and warmth of the AI. Future adaptations of our studies should keep this potential ambiguity in mind when designing manipulation scenarios.

We also concede that our manipulation checks, while statistically significant, showed relatively modest mean differences. For instance, in Study 3, the mean difference between the two manipulation conditions was only 0.16, which, despite a significant p-value of .045 and a small to medium effect size, could indicate the need for a more robust treatment to amplify the disparities between the conditions. This issue may stem from our use of entirely novel manipulation scenarios not previously tested in other studies. Thus, we lacked extensive empirical evidence for the efficacy of our manipulations. Future research can focus on enhancing and refining our manipulation scenarios, aiming to create more substantial distinctions between conditions.

Moreover, our understanding of how individuals perceive AI agents as utilitarian or hedonic remains a proposition, as we do not know the percentage of participants in our study who perceive AI agents as primarily utilitarian. Depending on participants' knowledge about the way AI operates, their perception of its utilitarian approach may vary (Niemelä et al., 2017; Hu, 2021). Furthermore, our study primarily focused on a homogenous demographic of management students from a large university, whose education and prior knowledge may influence their perception of AI's utilitarian and hedonic qualities. A recent study also found that although the majority of study participants were familiar with the term "artificial intelligence," yet relatively fewer participants were aware of its applications in recommender systems, search engines, and social media advertisements (Kozyreva, Lewandowsky, & Hertwig, 2020). Thus, it is important to control for these possibilities in future studies.

Another important consideration is that the perceived utilitarian nature of AI agents may be scenario-dependent and may be influenced by task complexity (Xie, Wang, & Cheng, 2022). In our research, we used task definitions with similar complexities, but in less complex tasks such as product recommendation, AI's assignment may be perceived as a less utilitarian, more hedonic addition to the base task. Task complexity appears as a compelling moderator candidate for future research to examine the suggested conceptual relationships in this research.

Additionally, moderate incongruency between AI agents and tasks may have a positive effect on people's support for AI (Heckler & Childers, 1992; Noseworthy & Trudel, 2011). Therefore, it is important to investigate our conceptual relationships at different levels of agent-task incongruency in future research.

Finally, past research has suggested that AI's humanlike qualities are a key factor in its acceptance (Wien & Peluso, 2021). However, individual-level differences may exist, as people with less social power may prefer agents with less humanlike features, as humanlike agents are more likely to recognize others' low power and take advantage of them (Kim & McGill, 2011). Similarly, those who enjoy isolation in performing certain tasks may prefer less human involvement in the task and have a positive attitude when AI's nonhuman qualities are more salient (Kim, Chen, & Zhang, 2016). Therefore, it is essential to investigate these individual-level differences in future research.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data was uploaded to an online repository and the link is shared in the article in the overview of studies section.

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