Management Research and Practice
Volume 18, Issue 3 / September 2026

HUMAN-LIKE INTERFACES AND PRODUCT TYPE EFFECTS

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Abstract
The growing adoption of automated digital interfaces, such as chatbots and virtual assistants, has made the management of human-like cues in digital customer interactions increasingly relevant for firms. Perceived human-like interaction cues, including empathy, social presence and relational support, may enhance trust, engagement and persuasive effectiveness in online contexts. However, less is known about when these cues represent an effective managerial lever, particularly with regard to product type. This study experimentally tests whether product type moderates the relationship between perceived human-like interaction cues and purchase intention. A between-subjects experiment was conducted with N = 100 participants, 50 per condition, exposed either to a personal product scenario related to wellbeing or to a functional product scenario related to management software. Perceived human-like interaction cues were measured as the average of Items 1–4, while purchase intention was measured as the average of Items 7–8. The results reveal a significant interaction between perceived human-like interaction cues and scenario: the association with purchase intention is stronger for the personal product than for the functional product, supporting a product–interaction congruence logic. From a managerial perspective, the findings indicate that the humanisation of digital interfaces should not be implemented as a uniform strategy, but calibrated according to product category and customer value expectations. The study contributes to digital management and customer experience management by clarifying the conditions under which human-like interfaces are effective and by offering guidance for category-specific interface design.
Keywords: human-like digital interfaces; customer experience management; social presence; product–interaction congruence; purchase intention.

1. INTRODUCTION

In recent years, the digital transformation of markets has profoundly reshaped purchasing processes, shifting an increasing share of consumer–firm interactions towards environments mediated by automated technologies, including chatbots, recommendation systems and conversational interfaces. For firms, these tools are not merely technological solutions for automation, but strategic components in the management of the digital customer experience. They are designed to improve the efficiency and continuity of the customer experience across the customer journey (Lemon & Verhoef, 2016; McLean et al., 2020). However, the absence of direct human contact may amplify psychological mechanisms that are typical of online purchasing, including perceived risk and relational distance from the brand, with potential consequences for conversion decisions (Featherman & Pavlou, 2003).

In response to these challenges, the literature has shown that the perception of "human" cues in digital interfaces – such as empathy, social presence and anthropomorphic cues – can strengthen trust, engagement and favourable behavioural intentions, including purchase intention (Qiu & Benbasat, 2009; Mende et al., 2019). Within this framework, the human-like experience can be defined as the set of communicative and social cues that make an automated interaction perceived as socially present and relational, bringing it closer to the typical patterns of human interaction (van Doorn et al., 2017; Araujo, 2018). From a managerial perspective, the human-like experience can therefore be interpreted as an interface design lever through which firms seek to compensate for the relational distance that characterises automated digital environments.

Despite the considerable attention devoted to this topic, the effectiveness of perceived human-like interaction cues does not appear to be generalisable to every context of use. Growing evidence suggests that their effectiveness depends on the congruence between interaction style and the value expected from the product. Products with high personal relevance – involving identity-related and emotional dimensions, such as health, wellbeing and lifestyle – appear to benefit more from relational cues than functional or technical products, where criteria of efficiency and instrumental utility tend to prevail (Kim & Sundar, 2012; Liang et al., 2023). It follows that the humanisation of digital interfaces should not be assumed to be a universally valid best practice, but should instead be evaluated as a contingent design and interaction management choice.

ISSN 2067- 2462

However, experimental evidence that tests in a controlled way the interaction between perceived human-like cues and product type in shaping purchase intention remains limited. This study seeks to address this gap by adopting an experimental design that considers product type as a moderator of the relationship between human-like experience and purchase intention. In other words, the study investigates whether the same interface humanisation strategy produces different effects depending on the product category and the type of value sought by the customer. More specifically, the following hypothesis is proposed:

H1 – Product type moderates the relationship between perceived human-like interaction cues and purchase intention, such that this relationship is stronger for personal products than for functional products. In operational terms, this implies greater "elasticity" of purchase intention to empathic-relational interface cues in the personal product context, with a steeper slope, and a more attenuated relationship in the functional product context.

Through a scenario-based experiment and a questionnaire administered to young adults aged between 18 and 34, this study aims to provide empirical evidence on when and for which product categories human-like design represents an effective lever in contemporary digital marketing. From a management perspective, the contribution of the study lies in proposing a category-based logic for managing digital interfaces: human-like cues should not be implemented uniformly, but should be calibrated according to product category, expected level of customer involvement and customer experience objectives along the online customer journey.

2. LITERATURE REVIEW

The contemporary e-commerce landscape is characterised by the growing integration of automated interfaces – including chatbots, intelligent FAQs and recommendation systems – designed to increase the efficiency and scalability of digital services (Lu et al., 2020). From a managerial perspective, these tools now represent a relevant component of customer–firm interaction management, as they influence not only operational efficiency but also the perceived quality of the digital customer experience. However, the automation of the purchasing experience introduces important psychological implications: the reduction of human contact may increase perceived distance, information uncertainty and perceived risk, all of which affect consumer evaluations and online conversion decisions (Featherman & Pavlou, 2003). In this context, cues of "humanness" in digital interaction – such as empathy, communicative warmth and engagement – can perform a relational compensation function, helping to restore trust and support purchase intention (Yoganathan et al., 2021; De Cicco et al., 2020). Recent developments in generative AI, hybrid intelligence and intelligent automation further reinforce the relevance of this issue. Digital interfaces are evolving from scripted automated tools into adaptive and conversational systems capable of producing personalised responses, supporting customer service and shaping customer experience across digital touchpoints (Baek, 2023; Petrescu & Krishen, 2023; Wirtz & Pitardi, 2023). This evolution makes the managerial question addressed in this study more salient: as interfaces become increasingly capable of simulating human-like interaction, firms need to understand when such cues create value and when they should instead be limited, redesigned or aligned with the product context.

A well-established stream of research has interpreted this phenomenon through the construct of perceived social presence, understood as the feeling that a social, human or human-like presence exists behind the interface, making the interaction more relational and less impersonal (Gefen & Straub, 2004; van Doorn et al., 2017; Araujo, 2018). From this perspective, interfaces that employ natural language, contextual responses or communicative personalisation may activate cognitive and affective processes typical of interpersonal interactions, influencing trust, satisfaction and attitudes towards the offering (Qiu & Benbasat, 2009; Holzwarth et al., 2006). Consistently, empirical evidence shows that users evaluate the experience more favourably and display stronger behavioural propensity when the interaction conveys empathy, relational quality and social intelligence, particularly in service and assistance touchpoints (Ben Mimoun et al., 2017; Luo et al., 2019; Zarouali et al., 2020; Gretry et al., 2017; Söderlund & Berg, 2020). For firms, this implies that social presence is not merely a perceptual feature of the interface, but a design variable capable of shaping the digital relationship with the customer.

Alongside social presence, the literature has examined the role of anthropomorphism – that is, the attribution of human traits to digital agents – as a lever that can improve the experience and strengthen the perceived

Management Research and Practice
Volume 18, Issue 3 / September 2026

relationship between user and system (Aggarwal & McGill, 2007; Blut et al., 2021; Seeger et al., 2021). However, studies converge in suggesting that the effectiveness of humanisation depends on contextual conditions and does not operate uniformly. In particular, the impact of human-like cues appears to vary according to the nature of the product and the expected degree of personal involvement: for products with symbolic, identity-related or wellbeing-related value, perceived empathy and the relational dimension of the interface play a stronger role; for technical or instrumental products, users may prioritise clarity, control and efficiency (Kim & Sundar, 2012). Consistently, Verhagen et al. (2014) show that personalisation and social presence are more effective when the offering is perceived as subjectively relevant, suggesting a mechanism of congruence between value expectations and interaction style. This perspective introduces a contingent interpretation of digital design: the same human-like configuration may generate different effects depending on the functional, symbolic or experiential value associated with the product.

This principle of product–interaction congruence is also central to the literature on the potential negative effects of humanisation. When relational design is perceived as inconsistent with the purpose of use – for example, excessive "humanness" in highly technical contexts – adverse reactions may emerge, including dissonance, reduced credibility or perceptions of inappropriateness, in some cases linked to dynamics similar to the "uncanny valley" (Ciechanowski et al., 2019). In parallel, contributions on the aesthetics and experiential quality of digital interfaces show that visual and presentation elements can activate affective and evaluative responses in users, influencing engagement and behavioural intentions, especially when the product has an experiential or identity-related component (Eroglu et al., 2003; Lavie & Tractinsky, 2004; Hassenzahl, 2004). Finally, the perceived quality of the interaction also depends on implementation-related aspects – such as transparency, response time and system adaptivity – which influence engagement and the overall evaluation of the digital experience (Blut et al., 2021; Chaves & Gerosa, 2020; Gnewuch et al., 2018). It follows that the management of human-like interfaces requires a balance between relationality, efficiency and coherence with use expectations. Despite this growing body of evidence, the literature does not provide a fully consistent account of when human-like interface cues improve customer responses. On the one hand, studies on social presence and anthropomorphism suggest that human-like cues can increase trust, engagement and favourable behavioural intentions. On the other hand, research on automation, perceived artificiality and the uncanny valley indicates that excessive or poorly contextualised humanisation may generate discomfort, scepticism or reduced credibility. This tension is particularly relevant in AI-powered commerce, where conversational agents are increasingly capable of producing natural, personalised and socially rich interactions, but where customers may also question the appropriateness, transparency or authenticity of such cues. Existing evidence therefore remains inconclusive because many studies examine human-like design as a general interface characteristic, while paying less attention to the fit between the interaction style and the type of product being offered. This study addresses this unresolved issue by treating product type as a boundary condition that shapes the effectiveness of perceived human-like cues.

Overall, the literature suggests that the perception of human-like cues in digital interfaces influences trust, engagement and purchase intention, while also indicating that such effects are contingent and depend on the context of use. However, comparative experimental evidence directly testing the interaction between perceived human-like cues and product type on purchase intention remains limited. The present study addresses this gap through a controlled experimental design that manipulates product type, personal versus functional, in order to estimate its moderating effect on the relationship between human-like experience and purchase intention. In doing so, the study connects the literature on social presence and anthropomorphism with a digital management issue: identifying when interface humanisation represents a useful lever and when, instead, it should be calibrated or restrained.

This study therefore develops a product–interaction congruence perspective, according to which the human-like design of digital interfaces should not be considered a universal best practice, but rather a contingent managerial choice whose effectiveness depends on the product category and the type of value sought by the customer. This perspective makes it possible to interpret the digital interface as a configurable managerial resource, to be designed in coherence with the positioning of the offering, the level of customer involvement and the objectives of customer experience management.

3. METHODOLOGY

3.1. Research approach and design

This study adopts a quantitative approach based on a between-subjects experimental design, aimed at estimating the association between perceived human-like interaction cues in digital interfaces and purchase intention, and at assessing whether this association varies according to the type of digital product, personal versus functional. The choice of an experimental design is consistent with the aim of the study, which is not limited to describing consumer perceptions but seeks to test a specific moderation relationship relevant to the management of digital interfaces. The use of a between-subjects design makes it possible to compare two experimental conditions while avoiding order effects, learning effects and direct comparison between scenarios, which may alter responses, for instance through demand characteristics. Internal validity is supported by the random assignment of participants to the experimental conditions, which reduces the risk of selection bias and increases the extent to which observed differences can be attributed to the experimental manipulation.

3.2. Literature review and instrument development

To provide a theoretical foundation for the model and ensure coherence between constructs and measures, a systematic literature search strategy was adopted between October and November 2025. The search was conducted in Scopus, Web of Science, Google Scholar and ProQuest, and included peer-reviewed articles published between 2015 and 2025. The search strategy used combinations of English-language keywords, including "human factor", "social presence", "empathy in AI", "anthropomorphic agents", "purchase intention", "interactive design", "digital customer experience" and "human-like interface". Inclusion criteria concerned language, disciplinary field – digital marketing, HCI, consumer psychology and digital management – and relevance to the context of digital interaction and consumer behaviour. Screening was conducted in two stages, first by title and abstract and then through a relevance assessment, reducing an initial corpus of approximately 100 studies to 25 contributions considered theoretically and methodologically relevant. These contributions informed the operational constructs used in the study: social presence, relational empathy, emotional engagement, perceived trust and purchase intention. These constructs guided the formulation of the questionnaire items and the definition of the experimental manipulation. In this way, the instrument was designed to connect perceptual dimensions of digital interaction with managerially relevant outcomes, such as trust, purchase propensity and recommendation.

3.3. Sample and data collection procedure

Data were collected in November 2025 through an online questionnaire created with Google Forms and distributed through social media channels, including Instagram, Facebook and LinkedIn, university mailing lists and communities focused on marketing and user experience. A non-probability convenience sampling approach was adopted, consistent with the experimental and exploratory nature of the study and with the target population of digitally competent young adults. The final sample consisted of 100 participants, randomly assigned to one of two experimental conditions: Scenario A (n = 50) and Scenario B (n = 50). Given the sample size and recruitment method, the findings should be interpreted as initial experimental evidence useful for identifying theoretically relevant relationships, rather than as estimates generalisable to the entire population of digital consumers.

Item-level missing values were observed. In Scenario A, the item concerning post-experience purchase intention was completed by 49 respondents, whereas in Scenario B the manipulation check was based on 48 responses. In the analysis, item-level descriptive statistics were calculated using the effective denominator for each item, following a pairwise approach, whereas multivariate models, including the moderated regression, were estimated using complete cases, following a listwise approach, in order to ensure consistency in coefficient estimation. Participation was voluntary and anonymous; before completing the questionnaire, participants provided informed consent and received instructions clarifying the scientific purpose of the study, confidentiality conditions and the absence of "right" or "wrong" answers.

3.4. Experimental manipulation and scenarios

The experimental manipulation concerned the independent variable "type of digital product" and was implemented through two hypothetical descriptive scenarios designed to elicit different levels of personal involvement. In Scenario A, participants were exposed to a personal product, oriented towards wellbeing and the emotional sphere, whereas in Scenario B they were exposed to a functional product, oriented towards productivity and operational management. Randomisation across conditions was adopted to reduce selection bias and strengthen internal validity. The experimental scenarios were designed to ensure a clear distinction between the personal and functional product conditions, while maintaining a comparable structure across conditions.

The effectiveness of the manipulation was assessed through a post-treatment manipulation check, corresponding to Item 10 in Table 1. The reports show that in Scenario A the product was predominantly recognised as "personal" by 68% of participants, while 18% classified it as "functional" and 14% selected "I don't know". In Scenario B, the classification converged on "functional" in 91.7% of available responses. The manipulation check therefore provides overall acceptable support for the intended distinction between the two conditions, while also highlighting a non-negligible degree of interpretative uncertainty in Scenario A. This issue was taken into account in the robustness analyses, for example by excluding "I don't know" responses or responses inconsistent with the assigned condition.

3.5. Questionnaire structure and validation

The questionnaire was organised into two sections. The first collected demographic and behavioural information – age, gender, employment/occupational status, education level and frequency of online purchases – in order to describe the sample and support controls and secondary analyses. The second section included a set of closed-ended items designed to measure the constructs derived from the literature: perceived human-like cues, social presence, empathy, communicative style and perceived support, emotional engagement, trust, purchase intention and recommendation. Nine items were measured on a five-point Likert scale, ranging from 1 = "Strongly disagree" to 5 = "Strongly agree", while one item was a categorical question aimed at verifying the manipulation.

TABLE 1 – QUESTIONNAIRE STRUCTURE AND OPERATIONAL OBJECTIVES

#	Item	Response format	Operational objective
1	The digital interface gave me the impression of communicating like a real person.	5-point Likert scale	Measures social presence and perceived interface humanisation
2	The interaction seemed empathetic, as if it understood my needs.	5-point Likert scale	Assesses perceived relational empathy
3	The language and tone used by the system were human and natural.	5-point Likert scale	Measures the human-like communication style of the interface
4	I perceived the presence of support, even though it was automated.	5-point Likert scale	Captures the implicit perception of social support
5	I felt emotionally engaged during the experience.	5-point Likert scale	Assesses emotional engagement
6	The experience conveyed trust to me.	5-point Likert scale	Measures trust in the system/interface
7	I would feel comfortable purchasing this product through this interface.	5-point Likert scale	Measures behavioural comfort with purchase
8	After this experience, I would be inclined to purchase the product.	5-point Likert scale	Directly measures purchase intention
9	I would recommend this website/app to others.	5-point Likert scale	Assesses satisfaction and word-of-mouth intention
10	In your opinion, which category does the product described belong to? Personal product / Functional product / I don't know	Multiple choice	Manipulation check for product type

Source: authors' elaboration.

Before the final administration, a pre-test (n = 10) was conducted to assess semantic clarity and comprehensibility. The feedback received led to minor terminological adjustments to reduce ambiguity and improve item clarity. The items were presented in a fixed order, with standardised instructions to reduce divergent interpretations, and were formulated neutrally in order to limit social desirability and acquiescence bias. Table 1 summarises the items, response format and operational objective. Items 1–4 were subsequently aggregated into the composite index of perceived human-like interaction cues, while Items 7–8 were used to construct the composite index of purchase intention.

3.6. Data analysis

Descriptive analyses were conducted using the exported questionnaire responses and associated spreadsheets. Frequencies, means and standard deviations were calculated for each item, together with checks for item-level missing values. The internal consistency of the scales was assessed using Cronbach's alpha and, where appropriate, composite indices were constructed as the average of the items belonging to the same construct. Specifically, perceived human-like interaction cues were operationalised as the average of Items 1–4, while purchase intention was operationalised as the average of Items 7–8.

The moderation hypothesis was tested by estimating a regression model including an interaction term between perceived human-like interaction cues and the experimental condition, namely product type. To facilitate coefficient interpretation, the continuous index of perceived human-like interaction cues was mean-centred before computing the interaction term; the model was estimated using complete cases for the composite dependent variable. The estimates were interpreted by considering both the main effects and the interaction term, which represents the direct test of H1. The manipulation check question was used to assess whether participants correctly perceived the product type and to conduct sensitivity and robustness analyses. This analytical strategy makes it possible to evaluate not only whether perceived human-like interaction cues are associated with purchase intention, but also whether this association changes according to the managerial context represented by the product category. For the moderated regression model, both unstandardised and standardised coefficients were examined. In addition, Cohen's f^2 was calculated from the change in explained variance between the main-effects model and the interaction model, in order to assess the substantive magnitude of the moderation effect.

Use of AI tools. During manuscript preparation, a large language model was used only for language editing, academic style refinement and formatting support. The tool was not used to generate original research data, statistical findings, interpretations of results or the literature review. All analytical decisions, data processing, results and final content were checked and approved by the author.

4. RESULTS

4.1. Data screening, balance across conditions and sample quality

A total of N = 100 observations were analysed, evenly distributed across the two experimental conditions: Scenario A (n = 50) and Scenario B (n = 50). Missing values were limited and restricted to individual items: in Scenario A, one missing value was observed for Item 8, relating to purchase intention, while in Scenario B two missing values were observed for the manipulation check, corresponding to Item 10. Consistent with the nature of the analyses, item-level descriptive statistics were calculated using the effective denominator for each item, following a pairwise approach, whereas the multivariate analyses using the composite purchase intention index, computed as the average of Items 7–8, were estimated using complete cases (N = 99). This procedure preserves the largest possible number of observations in the descriptive analyses while ensuring consistency in the estimation of multivariate models.

The comparability of the two conditions was assessed using chi-square tests of independence on the main demographic variables. Age groups were similar across Scenario A (18–24: 40; 25–29: 8; 30–35: 2) and Scenario B (18–24: 38; 25–29: 11; 30–35: 1), with no evidence of significant imbalance, $\chi^2(2) = 0.86$, $p = .651$. The gender distribution also did not differ significantly between conditions: Scenario A included 34 women and 16 men, while Scenario B included 30 women and 20 men, $\chi^2(1) = 0.39$, $p = .532$. Finally, occupational status was comparable across the two groups, $\chi^2(3) = 2.10$, $p = .552$. Overall, these checks support the assumption of initial equivalence between groups, strengthening the internal validity of the experimental comparison. This is particularly relevant because it allows the observed differences to be interpreted as more plausibly associated with the experimental manipulation of product type.

4.2. Manipulation check: perceived product type

The effectiveness of the "product type" manipulation was assessed through Item 10. In Scenario A, 34 participants, corresponding to 68%, classified the product as a "personal product", 9 participants, corresponding to 18%, classified it as a "functional product", and 7 participants, corresponding to 14%, selected "I don't know". In Scenario B, 44 participants classified the product as a "functional product", 1 participant as a "personal product", and 3 participants as "I don't know", in addition to 2 missing values. The manipulation check therefore provides overall acceptable support for the distinction between personal and functional products, while also highlighting a non-negligible degree of interpretative uncertainty in Scenario A. These incongruent or uncertain responses were explicitly considered in the robustness analyses, in order to assess the stability of the moderation effect with respect to manipulation quality.

4.3. Scale reliability and construction of composite indices

The internal consistency of the multi-item measures was assessed using Cronbach's alpha, calculated separately for each condition. The perceived human-like interaction cues index, constructed as the average of Items 1–4 – social presence, empathy, human/natural tone and perceived support – showed high reliability in Scenario A ($\alpha = .868$) and Scenario B ($\alpha = .855$), exceeding the commonly used threshold for acceptable internal consistency ($\alpha \geq .70$). The purchase intention measure, constructed as the average of Items 7–8, also showed high reliability in Scenario A ($\alpha = .876$) and satisfactory reliability in Scenario B ($\alpha = .775$). On the basis of this evidence, the subsequent analyses use the composite indices HumanFactor = average of Items 1–4 and PurchaseIntent = average of Items 7–8, the latter estimated on complete cases. The construction of composite indices reduces measurement error associated with individual items and allows the hypothesis to be tested using constructs that are consistent with the theoretical model.

4.4. Descriptive statistics by condition and differences between scenarios

The descriptive statistics reveal marked differences between conditions for the constructs most directly related to perceived human-like interaction cues and emotional engagement. Specifically, HumanFactor was higher in Scenario A ($M = 4.12$; $SD = 0.77$) than in Scenario B ($M = 2.58$; $SD = 0.96$). Emotional engagement, measured by Item 5, followed a similar pattern: Scenario A, $M = 4.08$; $SD = 1.01$; Scenario B, $M = 2.04$; $SD = 1.26$. Trust, measured by Item 6, was also higher in Scenario A ($M = 4.16$; $SD = 0.89$) than in Scenario B ($M = 3.74$; $SD = 0.90$). Outcomes closer to purchasing behaviour showed more modest differences: PurchaseIntent was higher in Scenario A ($M = 3.94$; $SD = 0.87$; $n = 49$) than in Scenario B ($M = 3.65$; $SD = 0.69$; $n = 50$), while recommendation, measured by Item 9, was higher in Scenario A ($M = 4.28$; $SD = 0.86$) than in Scenario B ($M = 3.82$; $SD = 0.80$).

Differences between conditions were assessed using Welch's t-tests, without assuming equality of variances. Effects were very large for HumanFactor ($t = 8.82$, $p < .001$, $d = 1.76$) and emotional engagement ($t = 8.94$, $p < .001$, $d = 1.79$), and moderate for trust ($t = 2.35$, $p = .021$, $d = 0.47$) and recommendation ($t = 2.77$, $p = .0067$, $d = 0.55$). For PurchaseIntent, the effect was positive but not statistically significant at conventional levels ($t = 1.83$, $p = .070$, $d = 0.37$), suggesting that the manipulation affected perceptual and emotional dimensions more strongly than declared conversion. This result is consistent with the idea that interface humanisation first acts on trust, engagement and relational perception, while its effect on purchase intention also depends on the congruence between product type and interaction style. Item-level tests are therefore interpreted as descriptive evidence supporting the hypothesis, while the main test is provided by the moderation model reported below.

4.5. Hypothesis testing (H1): moderation by product type

To test H1, a regression model including an interaction term between perceived human-like interaction cues and experimental condition was estimated. Purchase intention (PurchaseIntent) was operationalised as the average of Items 7 and 8, while perceived human-like interaction cues (HumanFactor) were calculated as the average of Items 1–4. The experimental condition was coded as a dichotomous variable (Scenario A = 1; Scenario B = 0). To facilitate coefficient interpretation and reduce collinearity between terms, HumanFactor was mean-centred before computing the interaction term (HumanFactor × Scenario). The analysis was conducted on N = 99 complete cases for the dependent variable, due to one missing value on Item 8 in Scenario A, and estimates are reported with HC3 robust standard errors.

The results of the models are reported in Table 2. Model 1 includes only the main effects, perceived human-like interaction cues and scenario, whereas Model 2 adds the interaction term. The inclusion of the interaction increases the explained variance ($R^2 = .300 \rightarrow R^2 = .378$; $\Delta R^2 \approx .078$). In Model 2, the main effect of HumanFactor is positive and statistically significant ($b = 0.268$, $p = .033$), indicating that, on average, higher perceived human-like interaction cues are associated with increased purchase intention. Crucially, the HumanFactor × Scenario interaction term is positive and significant ($b = 0.521$, $p = .0065$), indicating that the relationship between perceived human-like interaction cues and purchase intention is stronger in Scenario A, involving the personal product, than in Scenario B, involving the functional product.

The interpretation through simple slopes confirms the moderation effect: in Scenario B, that is, when Scenario = 0, the slope of HumanFactor on PurchaseIntent is $b = 0.268$ ($p = .036$), whereas in Scenario A, that is, when Scenario = 1, the slope is higher, $b = 0.268 + 0.521 = 0.789$ ($p < .001$). Overall, the results support H1, indicating that the effectiveness of perceived human-like interaction cues in supporting purchase intention is greater when the product is personal rather than functional. From a managerial perspective, this finding suggests that the same interface humanisation strategy may generate different returns depending on the product category, being particularly effective when the product activates personal, emotional or identity-related needs.

TABLE 2 – REGRESSION MODELS FOR TESTING H1

Variables	Model 1 b (SE)	P	95% CI	Model 2 b (SE)	P	95% CI
Constant	4.011 (0.144)	< .001	[3.728; 4.294]	3.856 (0.166)	< .001	[3.530; 4.182]
Humanfactor_c	0.471 (0.101)	< .001	[0.273; 0.668]	0.268 (0.126)	.033	[0.021; 0.515]
Scenario (A = 1)	-0.430 (0.254)	.091	[-0.928; 0.068]	-0.517 (0.233)	.026	[-0.974; -0.060]
Humanfactor_c × Scenario	–	–	–	0.521 (0.192)	.0065	[0.146; 0.897]

HC3 robust standard errors
Dependent variable: PurchaseIntent, average of Items 7–8; N = 99
Predictors: HumanFactor_c, mean-centred average of Items 1–4; Scenario, A = 1 and B = 0; interaction
$R^2 = .300$ in Model 1; $R^2 = .378$ in Model 2; $\Delta R^2 \approx .078$.

Source: authors' elaboration.

To improve the interpretability of the moderation model, standardised coefficients and an additional effect size for the interaction were also examined. In Model 2, the standardised coefficient for perceived human-like interaction cues was positive ($\beta = .393$), as was the standardised coefficient for the interaction term HumanFactor_c × Scenario ($\beta = .438$), while the standardised coefficient for Scenario was negative ($\beta = -.332$). The moderation effect size was estimated using Cohen's f^2, calculated from the increase in explained variance between Model 1 and Model 2. The interaction increased explained variance from $R^2 = .300$ to $R^2 = .378$, corresponding to $\Delta R^2 = .078$ and $f^2 = .125$. This value indicates an effect between small and medium magnitude, suggesting that the moderation is not only statistically significant but also substantively meaningful.

To facilitate interpretation of the interaction, Figure 1 displays the predicted values of PurchaseIntent as a function of mean-centred HumanFactor in the two experimental conditions.

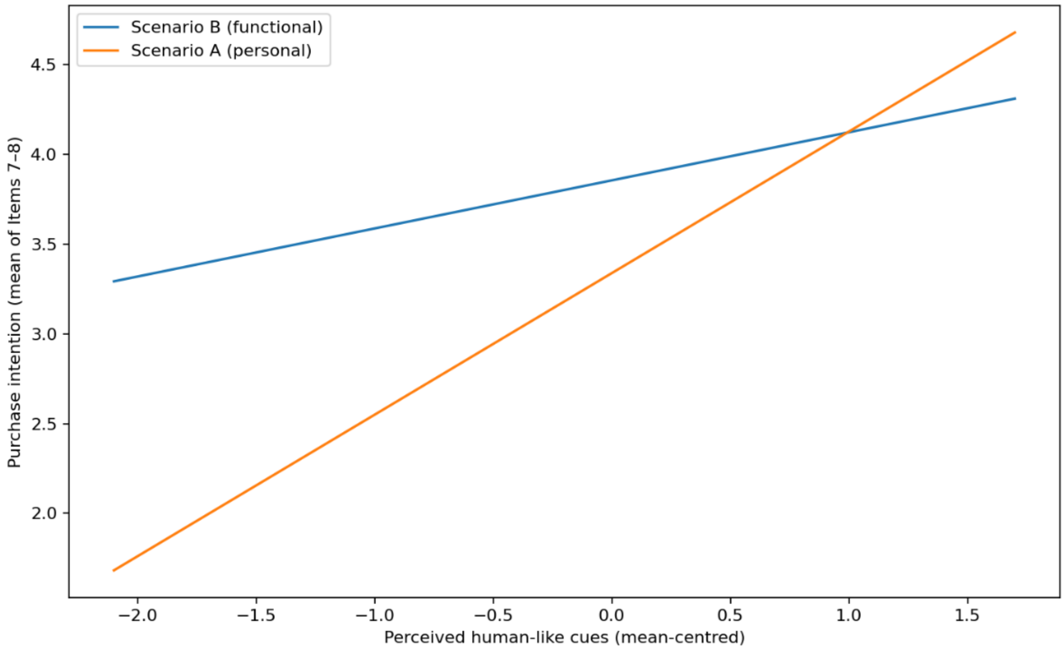

FIGURE 1 – PREDICTED VALUES OF PURCHASE INTENTION AS A FUNCTION OF PERCEIVED HUMAN-LIKE CUES, SEPARATELY FOR SCENARIO A, PERSONAL PRODUCT, AND SCENARIO B, FUNCTIONAL PRODUCT
Source: authors' elaboration.

4.6. Robustness checks

Two sensitivity analyses were conducted to assess the stability of the moderation effect with respect to the quality of the manipulation. In the first check, excluding "I don't know" responses and missing values on the manipulation check, the interaction remained positive and reached the conventional significance threshold (b = 0.351, p = .050), indicating directional stability of the effect. In the second check, adopting a per-protocol criterion, that is, including only respondents who correctly classified the product in line with their assigned scenario, the interaction retained a positive sign but was no longer statistically significant (p = .394). This result is consistent with the reduction in sample size and the consequent increase in standard errors, and therefore with lower statistical power. Overall, the robustness analyses confirm the direction of the moderation effect and make transparent the sensitivity of the estimate to particularly restrictive filters on the manipulation check. The findings should therefore be interpreted as evidence consistent with the product–interaction congruence hypothesis, while maintaining caution regarding the generalisability of the effect under more selective manipulation criteria or in larger samples.

5. DISCUSSIONS AND MANAGERIAL IMPLICATIONS

The findings of this study provide empirical support for a product–interaction congruence perspective, according to which the effectiveness of human-like digital interfaces depends on the alignment between the characteristics of the interaction and the type of value expected from the product. In this sense, the contribution of the study lies not only in showing that perceived human-like interaction cues are associated with purchase intention, but also in clarifying that this association varies according to product category. This evidence strengthens a contingent view of digital interface management, in contrast to standardised approaches that treat humanisation as a universally positive lever.

Theoretically, the findings refine the application of Social Presence Theory and anthropomorphism research in digital commerce by showing that the effectiveness of human-like cues is conditional rather than universal. Human-like design does not simply increase purchase intention because it makes the interface more social or more anthropomorphic; rather, its effect depends on whether the relational meaning of the interaction fits the value logic of the product. This extends prior work by positioning product type as a boundary condition that determines when social presence becomes persuasive and when it may be less central to customer evaluation.

The study therefore contributes to a more contingent understanding of AI-mediated customer interaction, in which the managerial value of humanisation depends on the alignment between interface cues, product category and customer expectations.

The results also have implications for AI-powered commerce, conversational agents and generative AI systems. As firms increasingly deploy AI-enabled chatbots and virtual assistants capable of producing natural, personalised and emotionally nuanced responses, the question is no longer only whether interfaces should appear human-like, but when and to what extent such humanisation is appropriate. The findings suggest that generative AI-enabled interfaces may create greater value in categories where customers seek reassurance, empathy and personal relevance, while in functional categories they should prioritise clarity, task efficiency, transparency and perceived competence. This distinction is important for conversational commerce because the same AI capability may produce different customer outcomes depending on the product context in which it is deployed.

The results indicate that the humanisation of digital interfaces does not operate as a uniform lever, but produces effects that are contingent on the offering context. More specifically, the experimental evidence supports a logic of differentiation by product category: investment in relational cues - such as social presence, communicative empathy, natural tone and perceived support - should be allocated selectively, avoiding standardised and decontextualised human-like design strategies.

At a strategic level, for high-involvement personal categories, such as wellbeing, health, lifestyle and services associated with identity and self-care, the interface represents a touchpoint with high relational potential. Empathic communicative cues and forms of support perceived as “present” may help reduce uncertainty and psychological distance, strengthening not only purchase propensity but also broader relational outcomes, such as trust and advocacy. In such contexts, design should prioritise tone consistency and relational continuity across the digital customer journey, for example through conversational assistance, support-oriented microcopy, onboarding processes that recognise users’ needs and goals, and coherent post-interaction follow-up. These choices make it possible to transform the interface from a mere information channel into a relational space capable of supporting customer engagement.

For functional and instrumental products, the results suggest a different picture: although the association between perceived human-like interaction cues and purchase intention remains positive, the effect is more attenuated, indicating that users may place greater weight on utility, clarity and reliability. It follows that, in these categories, the human-like experience should be designed as competent, task-oriented support rather than as a relational experience. In operational terms, priority should be given to elements that signal control and performance – information clarity, reduced cognitive effort, immediate feedback and functional transparency – while empathic cues should be calibrated in a restrained way and aligned with the instrumental goal of the interaction. Excessive relational emphasis may in fact appear redundant or inconsistent with use expectations and may reduce the persuasive effectiveness of the interface. For managers, this implies that, in functional contexts, humanisation should reinforce the perceived competence of the system, rather than substitute operational clarity and information quality.

These findings converge on a central managerial implication: the design of humanised interfaces should follow a principle of product–interaction congruence, understood as the alignment between the value expected from the product and the intensity of the interface’s relational cues. For organisations, this implies adopting design and communication practices based on category segmentation, defining differentiated standards – in terms of tone, degree of personalisation, conversational design and type of support – according to the subjective relevance of the offering. In this way, the interface becomes a strategic component of the digital offering rather than a “neutral” communication module replicated across heterogeneous products. Interface management should therefore be integrated into decisions concerning positioning, customer experience and service design, rather than being delegated exclusively to technical or graphic design choices.

From a measurement perspective, the findings suggest that the human-like experience should be evaluated through a multi-level set of indicators: not only conversion and purchase intention, but also intermediate metrics such as trust, perceived support and engagement, as well as relational outcomes such as recommendation propensity. The observed moderation makes a continuous experimental approach particularly relevant, based on A/B testing and multivariate tests segmented by product category. The same humanisation intervention may produce different effects in personal and functional contexts, and targeted experimentation enables firms to accumulate replicable internal evidence and allocate design resources where the expected return is higher. In practical terms, firms should avoid evaluating human-like interfaces solely through aggregate KPIs, as overall averages may conceal differentiated effects across product categories.

Finally, sustainable human-like design requires attention to transparency and perceived control. In contexts where humanisation involves greater personalisation and conversational interaction, an execution perceived as opaque or intrusive may undermine trust and purchase intention, especially when users evaluate the trade-off between service benefits and privacy risks (Xu et al., 2009). Therefore, firms should integrate relational cues with practices of communicative clarity, such as disclosing automated interaction where relevant, minimising data collection and providing control over preferences, especially in more sensitive categories such as wellbeing and health. The managerial dimension of humanisation therefore concerns not only persuasive effectiveness, but also the ability to preserve trust, perceived control and the acceptability of digital interaction.

In summary, the study indicates that perceived human-like interaction cues represent a relevant managerial lever, but that their effectiveness depends on the alignment between the intensity of humanisation and the type of value expected from the product. For personal products, empathy and social presence may act as amplifiers of purchase propensity and of the relationship with the brand; for functional products, humanisation is more effective when it supports efficiency and perceived competence, without exceeding the level of relational cues required by the context. The main implication for management is therefore to adopt a category-based logic in the design of digital interfaces, calibrating the degree of humanisation according to the role played by the product in the customer experience.

6. CONCLUSIONS

This study examined the role of perceived human-like interaction cues in digital interfaces and their relationship with purchase intention, showing that the effectiveness of experience humanisation is not uniform, but depends significantly on the product context. More specifically, the empirical evidence supports a model in which product type, personal versus functional, acts as a contextual variable capable of modifying the strength of the relationship between perceived human-like interaction cues and purchase propensity, consistently with a fit logic between the value expected from the product and the relational style of the interaction. This finding contributes to the literature on human-like experience in digital contexts, which often tends to treat “human” cues as generalisable drivers, by instead highlighting a more selective mechanism conditioned by use expectations. From this perspective, the paper also contributes to the debate on digital management, as it interprets interface humanisation as a design and managerial choice to be calibrated according to the category of the offering.

At the theoretical level, the main contribution lies in providing empirical evidence of the moderating role of product type, suggesting that interface humanisation is particularly relevant when the offering is associated with identity-related, emotional or self-care dimensions, whereas in functional products purchase intention appears to be relatively more anchored in instrumental evaluations, such as efficiency and reliability. At the managerial level, the findings imply the need for category-specific digital design and communication strategies, intensifying empathic and relational cues for personal products while prioritising operational clarity and task-oriented support for functional products. The applied contribution of the study therefore lies in proposing a category-based logic for the management of digital interfaces, which may help firms avoid undifferentiated investments in human-like solutions and guide customer experience design decisions.

6.1. Limitations

The study nevertheless presents several limitations that constrain the generalisability of its conclusions. First, the sample size is limited. Although the between-subjects design is appropriate for testing the proposed moderation, an overall sample of N = 100, with 50 participants per experimental condition, provides only initial evidence and may limit the statistical power available to detect interaction effects. The significant interaction observed in the study should therefore be interpreted as encouraging but requiring replication with larger samples. Second, the use of a convenience sample of young adults aged 18–34 restricts the external validity of the findings. This demographic is likely to be relatively digitally literate and familiar with automated interfaces, chatbots and online purchasing environments. As a result, younger users may evaluate human-like cues, automated interaction and possible uncanny valley effects differently from older or less digitally experienced consumer segments. Their threshold for automated scepticism, discomfort or perceived artificiality may therefore differ significantly from that of other populations. Third, the manipulation was implemented through hypothetical scenarios rather than through real interactions with platforms or prototypes, with potential implications for ecological validity. Fourth, purchase intention was measured through self-reported indicators, with possible common method variance and social desirability effects, and not through observed behaviours such as click-through, actual choice or real conversion. Finally, the presence of a degree of uncertainty in the manipulation check for the personal scenario suggests that, in some cases, the distinction between personal and functional products may depend on individual differences, such as involvement, familiarity and perceived needs. Consequently, the findings should be interpreted as initial experimental evidence consistent with the product–interaction congruence hypothesis, rather than as a definitive estimate of the effect across all digital consumption contexts.

6.2. Future research

In light of these limitations, future research could extend the model in at least three directions. First, it would be useful to replicate the study with larger and more diverse samples in terms of age, digital literacy, professional profile and familiarity with automated interfaces. This would make it possible to assess whether the observed product–interaction congruence effect holds across consumer segments with different levels of technological familiarity and automated scepticism. Second, future studies could introduce behavioural measures and more realistic experimental settings, such as interactive prototypes, field experiments and A/B tests on landing pages, in order to increase the ecological validity of the findings. Third, further research could explore additional moderators and mediators, including product involvement, privacy sensitivity, dispositional trust towards automated systems, perceived authenticity of digital agents and perceived artificiality. It would also be relevant to analyse the role of managerial variables, such as sector, brand positioning, offering complexity and degree of service automation, in order to better understand the organisational conditions under which interface humanisation creates greater value.

In summary, the findings indicate that perceived human-like interaction cues represent a potentially relevant lever in digital marketing and digital experience management, but that their effectiveness depends on the alignment between the intensity of relational cues and the nature of the value expected from the product. The main message of the study is that human-like digital interfaces should not be designed according to a one-size-fits-all logic, but rather through a contingent and category-based approach capable of integrating efficiency, trust and customer relationship objectives.

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