

From Design to Contribution: How AI Chatbots Shape Value Co-Creation in Online Retail in Morocco

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Abstract

Artificial intelligence (AI) chatbots are now central to online retail, yet little is known about how their specific design attributes enable customer value co-creation (VCC), or whether these links hold across cultures. Drawing on service-dominant (S-D) logic, cross-cultural consumer research, and the DART (dialogue, access, risk assessment, transparency) model, this study develops and tests a framework that links five chatbot design attributes to the four DART dimensions and, in turn, to customer outcomes. Survey data from 562 online shoppers in Morocco with recent chatbot experience were analyzed using confirmatory factor analysis and structural equation modeling. Responsiveness and personalization drive dialogue; usability and information quality enhance access; personalization and information quality support risk assessment; and information quality is the dominant driver of transparency. Anthropomorphism (human-likeness) has no significant effect on dialogue. Dialogue and access increase customer satisfaction, which in turn strongly predicts loyalty and purchase intention. The study extends S-D logic to human–AI interaction. Read against Morocco’s culture and developing e-commerce market, the results suggest that functional chatbot features are likely to work across markets, whereas social features such as human-likeness depend on culture. The study offers propositions for cross-country research and guidance on what global retailers should standardize or localize.

Keywords: *artificial intelligence; AI chatbots; value co-creation; cross-cultural consumer behavior; emerging markets; Morocco*

Date of Submission: 11-10-2026

Date of Acceptance: 23-10-2026

I. Introduction

AI chatbots have become standard in online shopping. As AI has moved from a side technology to a core part of business strategy (Manyika, 2022), chatbots have evolved from simple programs that answered basic questions from fixed scripts into AI-powered assistants that hold natural conversations, recommend products, and help customers complete purchases at any hour (Davitaia, 2025; Madanchian, 2024; Rana et al., 2021). This makes them a key point of contact between retailers and customers and a natural setting for value co-creation (VCC): the idea, rooted in service-dominant (S-D) logic, that value is not simply delivered by the firm but is created jointly through the customer’s interactions with it (Anshu et al., 2021; A. Chen et al., 2021).

Yet little is known about how chatbots support co-creation. Prior studies have examined chatbot adoption (Taecharungroj, 2023) and its effects on satisfaction (J. Chen et al., 2021) and loyalty (Q. Chen et al., 2023), but few have examined individual chatbot design attributes or traced their effects on different dimensions of co-creation. A second gap concerns culture. Most evidence comes from developed Western and East Asian markets, even as retailers and technology vendors increasingly deploy the same chatbot designs across countries (Le et al., 2025). This practice assumes that a feature that works in one market will work in another. Both S-D logic and cross-cultural consumer research challenge this assumption: value is judged in context, and context varies across cultures (Akaka et al., 2013; de Mooij & Hofstede, 2011). Indeed, users in different countries weigh chatbot features differently and vary in how readily they perceive chatbots as human-like (Folk et al., 2025; Shin, Al-Imamy, et al., 2022). Whether chatbot design should be standardized or adapted across markets is a long-standing question in international marketing (Theodosiou & Leonidou, 2003) and therefore remains unresolved. Emerging markets are especially useful for addressing this question because their conditions differ from those in which most marketing theory was developed (Burgess & Steenkamp, 2006; Sheth, 2011).

Morocco offers a strong test case. Its culture scores high in power distance and uncertainty avoidance and tends toward collectivism (Hofstede et al., 2010). Communication relies heavily on context and relationships (Hall, 1976), while shoppers move between Darija (Moroccan Arabic), Modern Standard Arabic, French, and

Amazigh. Although online retail is growing, trust in online payments remains limited, and many shoppers still pay cash on delivery. These conditions differ sharply from those in Western markets, where most chatbot research is based.

This study examines how five chatbot design attributes—responsiveness, personalization, anthropomorphism (human-likeness), information quality, and usability—influence the four dimensions of co-creation in the DART model (dialogue, access, risk assessment, and transparency; Prahalad & Ramaswamy, 2004). It also considers how these dimensions, in turn, affect online shoppers' satisfaction, loyalty, and purchase intention in Morocco. The study makes three contributions. First, it identifies which chatbot attributes drive each co-creation dimension, positioning the chatbot as an active participant in service rather than merely a tool. Second, it offers a culture-sensitive perspective on chatbot-based co-creation by distinguishing functional features, expected to work across markets, from social features, whose effects depend on culture, and proposing that this distinction be tested across countries. Third, it provides global retailers with practical guidance on which aspects of chatbot design to standardize and which to adapt locally.

II. Literature review and hypothesis development

2.1 The evolution and role of AI chatbots in online retail

Chatbots have evolved from simple, script-following programs to AI systems that understand natural language, learn from interactions, and perform a wide range of tasks (Davitaia, 2025). Large language models (LLMs) such as GPT-4 have significantly expanded their capabilities, from creative writing and coding to detailed answers to complex questions (Lee et al., 2023; Taecharunroj, 2023). In online retail, chatbots play several roles. They act as virtual assistants, guiding customers from product discovery to checkout (Rana et al., 2021). They are a primary customer-service channel, answering common questions and resolving issues instantly without human staff, improving efficiency and reducing costs (Nicolescu & Tudorache, 2022). They also personalise the shopping experience: by analysing user data in real time, they can offer tailored product recommendations and promotions (Dai & Liu, 2024; Raji et al., 2024). Such fast, personalised interaction has been shown to improve the online customer experience (J. Chen et al., 2021).

2.2 Value co-creation and the DART framework

Value co-creation (VCC) is central to modern marketing and stems from S-D logic. It treats the customer not as a passive recipient of value but as an active partner in creating it (Alimamy & Gnoth, 2021). Value arises “in use,” as customers combine their own knowledge, effort, and experience with the resources the firm provides. To enable this, firms must offer channels and settings that invite customers to participate (Rodríguez-Ardura et al., 2024).

To put VCC into practice, Prahalad and Ramaswamy (2004) proposed the DART model, which identifies four building blocks of co-creation. *Dialogue* is two-way communication between customer and firm, in which both sides learn from each other rather than the firm simply broadcasting messages (Majeed, 2024). *Access* means giving customers the tools, information, and resources they need to take part, including access to systems and processes that were previously internal to the firm. *Risk assessment* means helping customers understand and manage the risks of their choices by giving them information on likely benefits and drawbacks. *Transparency* is the clarity and openness of information about a company's products, services, and processes; it builds trust and makes the relationship fairer. The DART model is therefore well suited to analyzing how technologies such as AI chatbots support VCC in online retail (Vinod et al., 2024).

2.3 How culture and market conditions shape co-creation

S-D logic holds that value is judged by the customer who experiences it and that co-creation is guided by institutions—the formal rules, social norms, and shared meanings that shape how people interact (Vargo & Lusch, 2016). These institutions differ from one country to another. Akaka et al. (2013) therefore argue that value in international markets must be understood in its cultural context: the same product, interface, or interaction can create different value in different countries because people interpret and use it differently. For AI chatbots, this means that a design attribute does not create value on its own; it does so only when customers, guided by their culture and local market conditions, find it useful for dialogue, access, risk assessment, or transparency. The four DART dimensions can thus be seen as general building blocks of co-creation, while the chatbot attributes that support them may vary by culture.

Cross-cultural consumer research identifies the cultural dimensions that help predict such differences (de Mooij & Hofstede, 2011; Steenkamp, 2001). Three matter most for chatbot interactions. *Uncertainty avoidance* reflects the extent to which members of a society feel threatened by ambiguous or unknown situations; in high uncertainty-avoidance cultures, people show a stronger need for structure, explicit rules, and expert information before acting (Hofstede et al., 2010). *Individualism–collectivism* shapes whether consumers expect interactions to

focus on themselves as individuals or on their social relationships, and how readily they trust impersonal sellers. *Power distance* reflects how readily people accept hierarchy and advice from sources they see as authorities. Communication context also matters: in high-context cultures, meaning is carried by relationships, tone, and shared understanding rather than by explicit words alone (Hall, 1976), which raises the question of whether a machine's scripted friendliness can replace genuine relational communication. Consistent with these arguments, comparative studies show that users in different countries, including the United States, Japan, and the United Arab Emirates, perceive and weigh chatbot features differently (Shin, Al-Imamy, et al., 2022; Shin, Chotiyaputta, et al., 2022), and that people's tendency to see chatbots as human-like varies across cultures (Folk et al., 2025).

Morocco combines these conditions in a way that differs from the markets where most chatbot research has been done. Hofstede et al. (2010) place Morocco high on power distance (70) and uncertainty avoidance (68) and in the middle, collectivist-leaning range on individualism (46). Everyday commerce is multilingual, so the language and tone a chatbot uses carry social meaning. Online retail also operates with limited trust in electronic payment and widespread cash on delivery (International Trade Administration, n.d.). This reflects weak market institutions what Khanna and Palepu (1997) call "institutional voids" in which the safeguards that support trust in mature e-commerce markets are lacking (Sheth, 2011). In such a setting, a retail chatbot can do more than serve customers: it can fill part of this trust gap by providing clear, verifiable information that shoppers cannot take for granted elsewhere.

This cultural view does not change the direction of the hypotheses below, which follow from S-D logic and prior chatbot research, but it makes testing them in Morocco more informative. If information-related attributes matter most where people dislike uncertainty and market safeguards are weak, their effects on access, risk assessment, and transparency should be strong here. Conversely, if human-like cues work only when they match local language and culture, generic human-like features may add little to dialogue in a high-context, multilingual market, even though studies elsewhere suggest a positive effect. The Moroccan case therefore shows not only whether the hypotheses hold, but also which relationships are likely to hold across cultures and which are likely to depend on them, a question we return to in Section 5.2.

2.4 Conceptual framework and hypotheses

We propose that, within a given cultural and market context, specific chatbot design attributes drive the dimensions of VCC. The model (Figure 1) links five chatbot attributes to the four DART dimensions, which in turn influence customer outcomes.

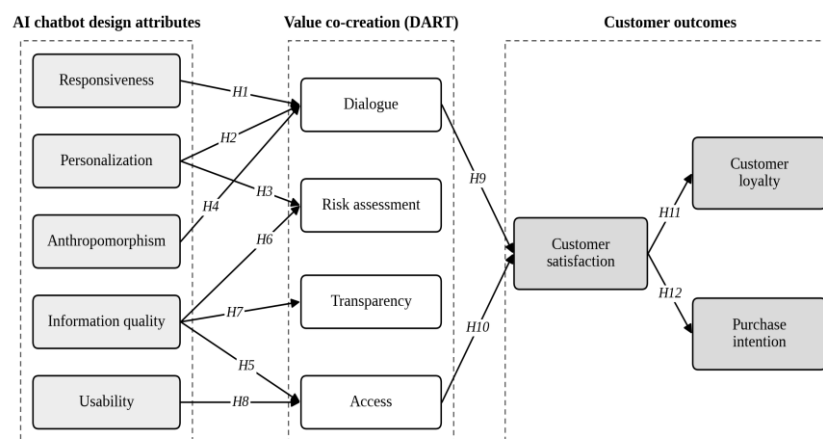


Figure 1. Conceptual model and hypotheses. The model is tested in Morocco's cultural and market context (see Section 2.3).

2.4.1 Chatbot design attributes and their influence on VCC

Responsiveness refers to the chatbot's ability to provide timely and prompt feedback to customer inquiries. The 24/7 availability and instantaneous nature of chatbots are among their primary benefits (J. Chen et al., 2021). A highly responsive chatbot fosters a continuous and fluid conversation, which is the essence of dialogue. When customers feel their input is immediately acknowledged and acted upon, they are more likely to engage in a sustained, interactive exchange.

H1: Chatbot responsiveness positively influences dialogue.

Personalization involves tailoring content, recommendations, and interactions based on a customer's individual data, such as past purchases, browsing history, and stated preferences (Ranjan & Upadhyay, 2024). Personalized

communication makes the conversation more relevant and meaningful, directly enhancing the quality of the dialogue. Furthermore, by providing customized information about product suitability and potential issues based on the user's profile, personalization helps customers in their risk assessment. In collectivist-leaning, high-context markets, personalized dialogue may also feel more relevant when it reflects the customer's social circle and language, not just individual preference data.

H2: Chatbot personalization positively influences dialogue.

H3: Chatbot personalization positively influences risk assessment.

Anthropomorphism is the attribution of human-like characteristics, intentions, or emotions to non-human agents such as chatbots (Solakis et al., 2022). Features such as a human name, an avatar, or conversational humor and empathy can make the interaction feel more like a social exchange. This human-like quality can encourage users to open up and engage in a more natural and extended dialogue (Mei et al., 2024). The strength of this effect, however, may depend on culture. The tendency to see technology as human-like, and preferences for social versus practical chatbot features, vary across countries (Folk et al., 2025; Shin, Al-Imamy, et al., 2022), and in high-context cultures (Hall, 1976), human-like cues that do not fit local language and customs may feel artificial. In line with most prior research, we nonetheless expect a positive effect and treat Morocco as a test of whether it holds.

H4: Chatbot anthropomorphism positively influences dialogue.

Information quality concerns the accuracy, completeness, and reliability of the information provided by a chatbot, which are essential (Labadze et al., 2023). High-quality information is fundamental to several VCC dimensions. It provides customers with the necessary resources to make informed decisions, thereby enhancing access. It is also the basis for effective risk assessment, as customers rely on this information to evaluate products. Finally, providing clear and honest information about products, policies, and pricing is the very definition of transparency. Inaccurate or "hallucinated" information, a known risk with LLMs, would severely undermine these processes (Gill et al., 2023). This role is likely to be especially important where uncertainty avoidance is high and e-commerce safeguards are weak, because shoppers then rely more heavily on the information the retailer itself provides (Hofstede et al., 2010; Khanna & Palepu, 1997).

H5: Chatbot information quality positively influences access.

H6: Chatbot information quality positively influences risk assessment.

H7: Chatbot information quality positively influences transparency.

Usability refers to the ease with which a customer can interact with the chatbot interface. A well-designed, intuitive interface reduces the mental effort required and removes barriers to interaction (J. Chen et al., 2021). If the chatbot is easy to use, customers can find information more effectively and complete the tasks they need, directly improving their access to the firm's resources and processes.

H8: Chatbot usability positively influences access.

2.4.2 The impact of VCC on customer outcomes

The ultimate goal of fostering VCC is to generate favorable outcomes for both the customer and the firm. When customers successfully engage in co-creation, their experience improves, leading to higher satisfaction (Constanza et al., 2025). A positive experience built on effective dialogue and easy access to resources is likely to result in a more satisfied customer. This satisfaction, in turn, is a well-established driver of customer loyalty and repeat purchase intention (Q. Chen et al., 2023). While risk assessment and transparency are crucial for building trust, their impact on immediate satisfaction might be less direct than that of the interactive dimensions of dialogue and access. Therefore, we focus on the latter as the primary drivers of satisfaction in a single interaction.

H9: Dialogue positively influences customer satisfaction.

H10: Access positively influences customer satisfaction.

H11: Customer satisfaction positively influences customer loyalty.

H12: Customer satisfaction positively influences purchase intention.

III. Methodology

3.1 Research design and sample

To test the proposed hypotheses, this study employed a quantitative, cross-sectional research design. The study developed an online survey to collect data from consumers who had experience interacting with AI chatbots on online retail websites or apps. The target population consisted of active online shoppers in Morocco. We used a combination of purposive and snowball sampling techniques to recruit participants. We sourced an initial pool of respondents from university student and staff mailing lists and online communities dedicated to e-commerce and technology. Participants were then encouraged to share the survey link with acquaintances who met the screening criterion (i.e., had used a retail chatbot within the last six months). This data collection strategy yielded

610 initial responses. After screening for incomplete surveys and responses from individuals who failed attention-check questions, we obtained a final sample of 562 usable questionnaires, resulting in a valid response rate of 92.1%. This sample size is considered adequate for conducting structural equation modeling (SEM) analysis.

3.2 Measurement instruments

The survey instrument was designed to measure the twelve constructs in the research model: five chatbot design attributes, the four dimensions of VCC (dialogue, access, risk assessment, transparency), and three customer outcomes (customer satisfaction, loyalty, purchase intention). All measurement items were adapted from established scales in prior literature to ensure content validity. Minor wording adjustments were made to fit the specific context of AI chatbot interactions in online retail. All items were measured on a 7-point Likert scale ranging from 1 (*strongly disagree*) to 7 (*strongly agree*).

Chatbot design attributes. Responsiveness (three items) was adapted from studies on system responsiveness. Personalization (four items) was based on scales measuring perceived customization in online services (Ranjan & Upadhyay, 2024). Anthropomorphism (three items) was adapted from research on the human-likeness of technology agents. Information quality (four items) drew on the information systems literature, focusing on accuracy, completeness, and relevance (Nguyen et al., 2023). Usability (three items) was adapted from the technology acceptance model literature, focusing on ease of use (J. Chen et al., 2021).

Value co-creation (DART). The four dimensions of VCC were measured using items adapted from studies measuring the DART dimensions. Dialogue (three items) focused on the interactivity and two-way nature of the conversation. Access (three items) measured the extent to which the chatbot provided the necessary information and tools. Risk assessment (three items) assessed the chatbot's role in helping users understand the pros and cons of a purchase. Transparency (three items) measured the perceived openness and honesty of the information provided. *Customer outcomes.* Customer satisfaction (three items) was measured using scales assessing overall satisfaction with the chatbot interaction. Customer loyalty (three items) was adapted from the marketing literature, focusing on intentions to reuse the service and recommend the brand (Q. Chen et al., 2023). Purchase intention (three items) measured the likelihood of making a purchase following the chatbot interaction (Dai & Liu, 2024).

3.3 Data analysis

The data analysis was conducted in two stages using IBM SPSS 26 and AMOS 26. First, descriptive statistics and correlation analysis were performed in SPSS to summarize the sample characteristics and examine the initial relationships between the variables. Second, a two-step SEM approach was employed. The first step involved a confirmatory factor analysis (CFA) to assess the reliability and validity of the measurement model. We evaluated convergent validity through factor loadings, average variance extracted (AVE), and composite reliability (CR). Discriminant validity was assessed using the Fornell–Larcker criterion (Fornell & Larcker, 1981). The second step involved testing the structural model to evaluate the hypothesized relationships between the constructs. The overall fit of the structural model was assessed using multiple goodness-of-fit indices, including the chi-square to degrees of freedom ratio (χ^2/df), the comparative fit index (CFI), the Tucker–Lewis index (TLI), and the root mean square error of approximation (RMSEA).

IV. Results

4.1 Sample demographics

Table 1 presents the demographic profile of the 562 respondents. The sample was relatively balanced by gender, with 53.4% identifying as female and 45.2% as male. The majority of respondents were young adults, with 68.1% falling into the 18–34 age group. The sample was well educated, with 75.8% holding a bachelor's degree or higher. Participants were frequent online shoppers, with 81.5% making online purchases at least once a month. Regarding their experience with the technology, 65.3% of respondents reported interacting with retail AI chatbots multiple times in the past six months, indicating a good level of familiarity with the subject of the study.

Table 1: Demographic profile of respondents (N = 562)

Characteristic	Category	Frequency	Percentage (%)
Gender	Male	254	45.2
	Female	300	53.4
	Other/prefer not to say	8	1.4
Age group (years)	18–24	198	35.2
	25–34	185	32.9
	35–44	101	18.0
	45–54	56	10.0
	55+	22	3.9

Characteristic	Category	Frequency	Percentage (%)
Education level	High school or less	35	6.2
	Some college/associate degree	101	18.0
	Bachelor's degree	288	51.2
	Master's degree or higher	138	24.6
Online shopping frequency	A few times a year	41	7.3
	Once a month	63	11.2
	2–3 times a month	195	34.7
	Once a week or more	263	46.8
Chatbot interaction frequency (past 6 months)	Once	195	34.7
	2–4 times	251	44.7
	5+ times	116	20.6

4.2 Descriptive statistics and correlation analysis

Table 2 presents the means, standard deviations (*SD*), and Pearson correlation coefficients for all latent constructs. Most constructs had mean scores above the 4.0 midpoint, suggesting generally positive perceptions of chatbot attributes and VCC experiences. The correlation matrix shows that all constructs are significantly and positively correlated ($p < .01$), providing preliminary support for the hypothesized relationships. All correlation coefficients were below the .80 threshold except for the satisfaction–loyalty correlation ($r = .81$), indicating that multicollinearity is not a major concern in this dataset.

Table 2: Means, standard deviations, correlations, and discriminant validity

Construct	<i>M</i>	<i>SD</i>	1	2	3	4	5	6	7	8	9	10	11	12
1. Responsiveness	5.21	1.15	.84											
2. Personalization	4.88	1.24	.58	.85										
3. Anthropomorphism	4.35	1.31	.45	.51	.88									
4. Information quality	5.33	1.18	.61	.65	.49	.86								
5. Usability	5.64	1.09	.63	.59	.47	.68	.89							
6. Dialogue	5.02	1.20	.69	.71	.55	.67	.64	.87						
7. Access	5.41	1.13	.65	.66	.50	.75	.78	.70	.85					
8. Risk assessment	4.79	1.25	.55	.69	.48	.72	.61	.65	.68	.83				
9. Transparency	4.95	1.28	.51	.60	.44	.79	.63	.61	.69	.74	.82			
10. Satisfaction	5.15	1.19	.62	.68	.53	.70	.69	.76	.74	.69	.65	.91		
11. Loyalty	4.98	1.26	.58	.64	.50	.66	.65	.71	.70	.65	.62	.81	.88	
12. Purchase intention	4.85	1.33	.54	.62	.49	.63	.61	.68	.66	.64	.59	.75	.78	.87

Note. $N = 562$. Diagonal values (in bold) are the square roots of the average variance extracted (AVE); off-diagonal values are inter-construct correlations, all significant at $p < .01$ (two-tailed).

4.3 Measurement model assessment

We conducted a CFA to assess the measurement model's validity and reliability. The results, shown in Table 3, indicate a good model fit: $\chi^2 = 1245.7$, $df = 548$, $\chi^2/df = 2.27$, CFI = 0.95, TLI = 0.94, RMSEA = 0.048. All standardized factor loadings exceeded the recommended threshold of 0.70 and were statistically significant ($p < .001$). The CR values for all constructs ranged from 0.86 to 0.93, exceeding the 0.70 benchmark. The AVE for each construct was above 0.50, ranging from 0.67 to 0.82. These results confirm the measurement model's convergent validity.

Table 3: Results of confirmatory factor analysis

Construct	Items	Loadings	Cronbach's α	CR	AVE
Responsiveness	RES1–RES3	0.82–0.89	0.87	0.88	0.71
Personalization	PER1–PER4	0.80–0.86	0.90	0.91	0.72
Anthropomorphism	ANT1–ANT3	0.85–0.91	0.90	0.91	0.77
Information quality	IQ1–IQ4	0.83–0.88	0.91	0.92	0.74
Usability	USA1–USA3	0.88–0.92	0.91	0.92	0.80
Dialogue	DIA1–DIA3	0.86–0.90	0.89	0.90	0.75
Access	ACC1–ACC3	0.84–0.89	0.88	0.89	0.73
Risk assessment	RSK1–RSK3	0.81–0.87	0.86	0.87	0.69
Transparency	TRN1–TRN3	0.79–0.85	0.85	0.86	0.67
Satisfaction	SAT1–SAT3	0.89–0.93	0.92	0.93	0.82
Loyalty	LOY1–LOY3	0.87–0.91	0.90	0.91	0.77
Purchase intention	PI1–PI3	0.85–0.90	0.89	0.90	0.75

Note. CR = composite reliability; AVE = average variance extracted.

Discriminant validity

Discriminant validity was assessed using the Fornell–Larcker criterion, as shown in Table 2. The square root of the AVE for each construct (the diagonal values) exceeds its correlation with any other construct (the off-diagonal values). This confirms that each construct is distinct from the others, establishing discriminant validity.

4.4 Structural model and hypothesis testing

We tested the structural model to evaluate the hypothesized paths. The model demonstrated a good fit to the data: $\chi^2 = 1489.2$, $df = 596$, $\chi^2/df = 2.50$, CFI = 0.94, TLI = 0.93, RMSEA = 0.052, with all indices meeting conventional thresholds ($\chi^2/df < 3.0$; CFI and TLI > 0.90 ; RMSEA < 0.08).

Drivers of VCC

As shown in Table 4, most hypotheses regarding the drivers of VCC were supported. Responsiveness ($\beta = 0.35$, $p < .001$) and personalization ($\beta = 0.41$, $p < .001$) significantly predicted dialogue. Personalization ($\beta = 0.38$, $p < .001$) and information quality ($\beta = 0.40$, $p < .001$) significantly influenced risk assessment. Information quality was the strongest predictor of both access ($\beta = 0.44$, $p < .001$) and, above all, transparency ($\beta = 0.81$, $p < .001$). Usability also had a strong positive effect on access ($\beta = 0.42$, $p < .001$). However, H4 was not supported, as anthropomorphism did not significantly affect dialogue ($\beta = 0.07$, $p = .098$).

Table 4: Results of hypothesis testing

Hypothesis	Path	β	SE	CR	p	Result
H1	Responsiveness → Dialogue	0.35	0.05	7.12	***	Supported
H2	Personalization → Dialogue	0.41	0.04	9.55	***	Supported
H3	Personalization → Risk assessment	0.38	0.05	7.98	***	Supported
H4	Anthropomorphism → Dialogue	0.07	0.04	1.65	.098	Not supported
H5	Information quality → Access	0.44	0.05	9.11	***	Supported
H6	Information quality → Risk assessment	0.40	0.05	8.33	***	Supported
H7	Information quality → Transparency	0.81	0.03	21.45	***	Supported
H8	Usability → Access	0.42	0.04	8.97	***	Supported
H9	Dialogue → Satisfaction	0.45	0.05	9.87	***	Supported
H10	Access → Satisfaction	0.39	0.05	8.54	***	Supported
H11	Satisfaction → Loyalty	0.84	0.03	25.11	***	Supported
H12	Satisfaction → Purchase intention	0.78	0.04	21.39	***	Supported

Note. β = standardized estimate; SE = standard error; CR = critical ratio. *** $p < .001$.

VCC and customer outcomes

Table 4 also shows strong support for the relationships between VCC dimensions and customer outcomes. Both dialogue ($\beta = 0.45$, $p < .001$) and access ($\beta = 0.39$, $p < .001$) significantly and positively predicted customer satisfaction. In turn, customer satisfaction strongly and positively influenced both customer loyalty ($\beta = 0.84$, $p < .001$) and purchase intention ($\beta = 0.78$, $p < .001$).

V. Discussion

This study examined how AI chatbot design contributes to value co-creation in online retail. The results largely support the proposed model. Retailers' design attributes strongly shape VCC: well-designed chatbots support co-creation, which raises customer satisfaction and, in turn, loyalty and purchase intention. Read against Morocco's cultural and market context, the results also suggest which parts of this chain are likely to work across markets and which will need local adaptation. The strongest predictors of dialogue were personalization and responsiveness: a conversation becomes a real dialogue when it is both timely and relevant to the individual (J. Chen et al., 2021). Customers value chatbots that respond quickly and understand their needs. By contrast, anthropomorphism did not significantly affect dialogue. Although users may appreciate a friendly tone, their main goal in retail is to solve problems efficiently (Chong et al., 2021); they care more about what the chatbot does than about how human it seems. In a task-focused setting, too much human-likeness may even feel distracting or fake, a possibility that deserves further study (Vo et al., 2024).

The Moroccan context helps explain this result. One might expect collectivist, high-context cultures to reward socially rich chatbots, yet a retail chatbot's human-likeness usually comes from generic cues, a name, an avatar, and scripted friendliness that may not match local ways of speaking, such as Darija, or local norms of politeness. In a high-context culture, where relationships are built on shared understanding rather than surface cues (Hall, 1976), such mismatched humanness may make the chatbot feel less like a real social partner. In addition, where people dislike uncertainty, shoppers may consult a chatbot mainly to reduce purchase risk rather than to socialize, which favors functional over social features. Because this study did not measure cultural values

directly, these explanations remain interpretive; however, they suggest that anthropomorphism's effect on dialogue depends on culture rather than being universal.

Information quality and usability most strongly influenced access. This highlights the importance of giving customers accurate, reliable information through an easy-to-use interface (Nicolescu & Tudorache, 2022). If the information is wrong or the interface is awkward, customers' ability to co-create value suffers. This aligns with research that identifies reliability and accuracy as key to the success of AI applications in education and other fields (Labadze et al., 2023). In a market where many shoppers still protect themselves by paying on delivery, easy access to accurate information through the retailer's own chatbot is likely to be especially valuable.

Risk assessment focused on both information quality and personalization. Customers feel more confident in their purchasing decisions when the chatbot provides trustworthy information tailored to their situation (e.g., "Based on your previous interest in hiking boots, this model has better ankle support"). This shows the chatbot's potential to act as a trusted advisor, a role once reserved for human sales staff (Ranjan & Upadhyay, 2024). This advisory role may matter even more in a high-power distance culture, where people readily accept advice from sources they see as competent and authoritative (Hofstede et al., 2010), although this idea needs to be tested across countries.

As expected, transparency depended almost entirely on information quality. This path ($\beta = 0.81$) was among the strongest in the model, showing that transparency in a chatbot interaction depends on whether its information is seen as truthful and complete (Aoki, 2020). Where market safeguards for online shopping are weak, the chatbot's information may partly make up for them, providing the clarity that shoppers in more mature e-commerce markets can obtain from the wider market (Khanna & Palepu, 1997; Sheth, 2011). This may help explain why the path is so strong in our data. Finally, VCC had strong effects on customer outcomes. Dialogue and access significantly increased satisfaction, suggesting that customers are most satisfied when they have had a relevant conversation and been given the tools and information to reach their goals (Anshu et al., 2021). Satisfaction in turn strongly predicted loyalty and purchase intention, confirming a well-established chain of effects in marketing in this new technological setting (Q. Chen et al., 2023).

5.1 Theoretical implications

This study makes several theoretical contributions. First, it tests and extends the DART model of VCC to human-AI interaction (Majeed, 2024). By identifying which chatbot design attributes drive each DART dimension, it offers a more detailed and practical account of how VCC emerges in digital settings, moving the discussion from conceptual argument to empirical evidence (Vinod et al., 2024). Second, it contributes to S-D logic by showing that an AI chatbot can act as an active resource that works on other resources to create value—what S-D logic calls an "operant" resource rather than serving as a passive tool (Lalicic & Weismayer, 2021). The chatbot participates in the service by engaging in dialogue, providing access, and helping customers manage risk. This perspective matters as AI becomes more autonomous and increasingly embedded in services (Solakis et al., 2022), and as chatbots spread across sectors, from education (Gill et al., 2023; Wang et al., 2023) to healthcare (Lee et al., 2023).

Third, the non-significant result for anthropomorphism adds nuance to research on human-computer interaction. While many studies stress the benefits of making technology more human-like (Meng & Dai, 2021), our results suggest that the effect depends on both the task and, as argued in Section 5.2, the culture. In goal-oriented online shopping, usefulness may matter more than sociability (Mei et al., 2024). This calls for a more critical view of making every AI system as human-like as possible and for matching design choices to user goals (Jeon, 2022).

5.2 Contributions to cross-cultural and global consumer marketing

The study also advances international and cross-cultural consumer marketing in three ways. First, it develops a culture-sensitive model of chatbot-based value co-creation. Research applying the DART model to AI has examined whether and how AI enables co-creation (Majeed, 2024; Vinod et al., 2024), but has given limited attention to the role of cultural context. Drawing on the S-D logic view that value depends on cultural context and is shaped by social rules and norms (Akaka et al., 2013; Vargo & Lusch, 2016), we argue that the DART dimensions are general building blocks of co-creation, while the chatbot attributes that enable them are filtered through national culture and local market conditions. This shifts the question from whether a design attribute works to where, and under what cultural and market conditions, it creates value. It thereby specifies the conditions under which the model applies, as any complete theory must (Whetten, 1989).

Second, the findings suggest a useful distinction between *functional features* and *social features* of chatbot design. Functional features (information quality, usability, and responsiveness) meet needs that consumers share across markets: accurate information, little effort, and quick answers. Their effects in our Moroccan sample align with those found in chatbot studies in other markets (J. Chen et al., 2021; Q. Chen et al., 2023). Social features (human-like cues, persona, and conversational style) rely on culture-specific meanings of politeness, relationships,

and language, and are therefore more likely to vary across markets. Personalization falls in between: it worked as a functional driver of dialogue and risk assessment in our data, but the kind of personalization customers find relevant and acceptable in terms of data use is likely to vary by culture. The non-significant effect of anthropomorphism in a collectivist-leaning, high-context market contrasts with prior research stressing the benefits of human-like chatbots (Meng & Dai, 2021) and fits evidence that the tendency to see chatbots as human-like differs across cultures (Folk et al., 2025). This distinction should therefore be tested across countries rather than treated as a universal design rule.

Third, the study extends international marketing research on emerging markets (Burgess & Steenkamp, 2006; Sheth, 2011) to chatbot-based service. Where market safeguards are weak, a retail chatbot's value may lie less in imitating a human salesperson than in compensating for missing safeguards by providing clear, verifiable information on products, policies, and prices. The central role of information quality across access, risk assessment, and transparency, and the very strong information quality–transparency path ($\beta = 0.81$), are consistent with this *trust-building role*. This links chatbot design to the broader market environment, a connection chatbot research, largely focused on mature markets, has so far overlooked.

To allow these arguments to be tested across countries, we offer four propositions:

P1: The positive effects of functional chatbot attributes (information quality, usability, and responsiveness) on the DART dimensions of value co-creation are similar across national cultures.

P2: The effect of chatbot anthropomorphism on dialogue depends on culture: it is stronger when human-like cues match local language and communication norms and when consumers readily see technology as human-like, and weaker when generic human-like cues are used in high-context cultures.

P3: The effects of chatbot information quality on risk assessment and transparency are stronger in markets with higher uncertainty avoidance and lower trust in e-commerce.

P4: The effect of personalization depends on individualism–collectivism: personalization based on individual preference data works better in individualistic cultures, whereas personalization that reflects the customer's social circle and language works better in collectivist cultures.

Together, these propositions specify the cultural and market conditions under which the model holds and turn a single-country study into a starting point for comparative research across cultures.

5.3 Managerial implications

The findings offer clear guidance for online retailers and chatbot developers. Investment should first go to chatbots' functional capabilities. Making sure that the information is accurate and complete (information quality), the system is intuitive (usability), it responds instantly (responsiveness), and it can tailor the interaction (personalization) is likely to yield the greatest gains in VCC and customer satisfaction (Dai & Liu, 2024; Rodríguez-Ardura et al., 2024). A friendly persona is not harmful in itself, but it should not come at the expense of these basic attributes (Tran et al., 2021). Information quality deserves particular attention. It requires the chatbot to be connected to up-to-date product databases, inventory systems, and customer relationship management (CRM) systems (Rana et al., 2021). Retailers must also train and refine their AI models to reduce errors and invented answers ("hallucinations"), which can destroy trust instantly and undermine VCC (Gill et al., 2023).

To strengthen dialogue, chatbots should do more than answer simple questions (Taecharungroj, 2023). They should ask clarifying questions, remember earlier interactions, and offer relevant information unprompted, turning a simple query into an advisory conversation (Haristiani, 2019). Retailers should view their chatbots as tools that put customers in control (A. Chen et al., 2021). An easy-to-use chatbot with high-quality information enables customers to help themselves, compare options openly, and decide with greater confidence, improving their experience and sense of control (Hsu et al., 2021). Instead of relying solely on traditional measures such as resolution time or the number of interactions, managers should track chatbot performance across each DART dimension. For example, they could measure the success rate of personalized recommendations (risk assessment), the number of conversational turns (dialogue), or user ratings of information clarity (transparency) (Gupta & Khan, 2024).

For multinational retailers, global marketplaces, and chatbot vendors, the findings support standardizing functional features and localizing social features. Functional features (accurate and complete information, intuitive interaction, and quick responses) can be set as a global standard and managed centrally, because our results show that they drive co-creation even in a cultural and market context quite different from those in which chatbot design norms were developed. Social features should be adapted locally. In Morocco, this means enabling chatbots to understand and reply in the languages and styles customers actually use, including Darija, French, and mixtures of the two, and adjusting tone, persona, and politeness to local norms rather than importing a generic human-like persona. Spending heavily on human-like features without such adaptation is unlikely to pay off.

In emerging markets where shoppers protect themselves by paying on delivery, chatbots can also serve as a trust-building tool. Clear, proactive information on delivery, payment options, returns, and product authenticity addresses exactly the points where shoppers' trust is weakest, so plans for entering and adapting to such markets

should prioritize the chatbot's information over its persona. Finally, managers should not assume that chatbot performance benchmarks from their home market apply elsewhere; the DART-based measures proposed above should be tracked by country and by language to show where adaptation is needed.

5.4 Limitations and future research

This study has several limitations that point to future research. First, its cross-sectional design captures a single point in time and cannot establish causality. Longitudinal studies tracking customer perceptions and VCC behaviors across multiple chatbot interactions would show how trust and loyalty develop over time (Constanza et al., 2025). Second, the data were collected through self-report surveys, which may be subject to common method bias and social desirability bias. Future research could employ experimental designs, A/B testing different chatbot features (e.g., a highly anthropomorphic vs. a purely functional chatbot) to isolate causal effects more rigorously. Physiological methods, such as eye-tracking or measuring skin conductance, could also provide objective measures of customer experience (Roemer et al., 2026).

Third, our sample was drawn from a single country, Morocco, and cultural factors may influence perceptions of AI and communication styles (Stöhr et al., 2024). Moreover, cultural values were not measured for individual respondents, so the cultural interpretations in Section 5 are based on theory rather than directly tested, and national culture scores hide differences within the country across regions, generations, and language groups. Future research should test the propositions in Section 5.2 with samples from several countries that differ in uncertainty avoidance, individualism, communication style, and e-commerce maturity—for example, Morocco and other Middle Eastern, North African, and Sub-Saharan African markets alongside European and East Asian markets where AI adoption is growing rapidly (Le et al., 2025). Such studies should first confirm that the survey measures mean the same thing in each country (measurement invariance; Steenkamp & Baumgartner, 1998), measure cultural values for each respondent (Yoo et al., 2011), and treat the language of chatbot interaction as a design variable in its own right.

Finally, this study focused on the positive aspects of VCC. Future research should also explore the potential for value co-destruction, where chatbot failures, privacy concerns, or poor design lead to negative customer experiences and value loss (Castillo et al., 2022). Understanding the causes and consequences of these negative outcomes, as well as the ethical considerations involved (Stark, 2023), is just as important as understanding the drivers of success. The integration of AI in various sectors, including art museums (Avlonitou et al., 2025) and higher education (Robayo-Pinzón et al., 2023), shows that these challenges are universal.

VI. Conclusion

This study examined how the design of AI chatbots contributes to value co-creation in online retail, using survey data from 562 online shoppers in Morocco. The results show that functional design attributes, including responsiveness, personalisation, information quality, and usability, drive the DART dimensions of co-creation, whereas anthropomorphism does not significantly foster dialogue. Information quality emerged as the most influential attribute, shaping access, risk assessment, and transparency. Dialogue and access, in turn, increase customer satisfaction, which strongly drives loyalty and purchase intention. By positioning the chatbot as an active participant in co-creation, the study extends S-D logic and the DART framework to human–AI interaction in an emerging market. Viewed in their cultural context, the findings suggest that functional chatbot features are likely to work across cultures and markets, whereas social features depend on culture; the propositions based on this distinction offer a starting point for cross-country research. For retailers, the findings indicate that investments in accurate information, ease of use, speed, and relevant personalisation are more likely to generate co-created value than efforts to make chatbots appear human; for global marketers, they support standardising these functional capabilities across markets while localising chatbot language and persona.

Funding

No funding was received.

Disclosure statement

The author reports there are no competing interests to declare.

Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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