Revue Internationale des Sciences de Gestion
ISSN: 2665-7473
Volume 8 : Numéro 4

UGC or Chatbot? Two Strategies, One Goal: How UGC and Chatbots Divergently Reduce Online Product Uncertainty

UGC ou Chatbot ? Deux stratégies, un objectif : Comment l'UGC et les chatbots réduisent différemment l'incertitude liée aux produits en ligne

MEDIMAGH Safa
High Institute of Management, Tunis, Tunisia
University of Tunis
Tunisia

Date submitted : 03/09/2025

Date of acceptance : 25/11/2025

To cite this article :

MEDIMAGH. S (2025) «UGC or Chatbot? Two Strategies, One Goal: How UGC and Chatbots Divergently Reduce Online Product Uncertainty», Revue Internationale des Sciences de Gestion « Volume 8 : Numéro 4 » pp : 188 - 213

Abstract

This study scrutinizes two predominant uncertainty reduction strategies in online retail: User-Generated Content (UGC) which stems from active strategy and chatbots which functions as an interactive strategy. Drawing on Uncertainty Reduction Theory (URT) and analyzing data from 455 online shoppers using Covariance-Based Structural Equation Modeling (CB-SEM), we examine how these strategies reduce product uncertainty across three dimensions (description, performance, fit) and influence purchase intention. Results reveal that UGC characteristics (trustworthiness, valence, information richness) significantly reduce all uncertainty types, with information richness being particularly impactful for performance (β=0.38) and description (β=0.42) uncertainty. Chatbot dimensions show more specialized effects: while anthropomorphism and social presence reduce fit uncertainty (β=0.27, β=0.28), media richness shows no significant effect on performance or description uncertainty. The findings demonstrate UGC's comprehensive uncertainty reduction capabilities versus chatbots' specialized effectiveness for fit-related uncertainty, providing theoretical and practical insights for optimizing online retail strategies.

Keywords: Uncertainty Reduction Theory, User-Generated Content, Chatbots, Product Uncertainty, Purchase Intention, CB-SEM.

Résumé

Cette étude examine deux stratégies prédominantes de réduction de l'incertitude dans le commerce de détail en ligne : le Contenu Généré par les Utilisateurs (UGC), qui relève d'une stratégie active, et les chatbots, qui fonctionnent comme une stratégie interactive. En s'appuyant sur la Théorie de la Réduction de l'Incertitude (URT) et sur l'analyse des données de 455 acheteurs en ligne via une modélisation par équations structurelles (CB-SEM), nous examinons comment ces stratégies réduisent l'incertitude produit selon trois dimensions (description, performance, adéquation) et influencent l'intention d'achat. Les résultats révèlent que les caractéristiques de l'UGC (fiabilité, valence, richesse informationnelle) réduisent significativement tous les types d'incertitude, la richesse informationnelle étant particulièrement influente sur l'incertitude performance (β=0.38) et description (β=0.42). Les dimensions des Chatbots montrent des effets plus spécialisés : si l'anthropomorphisme et la présence sociale réduisent l'incertitude d'adéquation (β=0.27 ; β=0.28), la richesse des médias n'a aucun effet significatif sur l'incertitude performance ou description. Les conclusions démontrent les capacités globales de réduction de l'incertitude par l'UGC, contrairement à l'efficacité spécialisée des Chatbots pour l'incertitude d'adéquation, offrant ainsi des insights théoriques et pratiques pour optimiser les stratégies de vente en ligne.

Mots clés : Théorie de la réduction de l'incertitude, contenu généré par les utilisateurs, Chatbots, incertitude liée au produit, intention d'achat, modélisation par équations structurelles basée sur la covariance (CB-SEM).

Introduction

The digital marketplace presents unique challenges for consumers, primarily stemming from the inability to physically inspect products before purchase (Featherman & Pavlou, 2003; Kim and Krishnan, 2015; Sun et al., 2022; Tang and Lin, 2019; Wang et al., 2022). This limitation creates significant product uncertainty that can hinder purchase decisions and lead to shopping cart abandonment (Wang et al., 2022). Uncertainty Reduction Theory (URT) posits that individuals actively seek information to reduce uncertainty in unfamiliar situations (Berger & Calabrese, 1975). In online retail, consumers employ various strategies to mitigate perceived risks, with User-Generated Content (UGC) and chatbots emerging as two prominent approaches.

UGC represents an active uncertainty reduction strategy where consumers proactively seek information from peer-generated content such as reviews, photos, and videos (Cheong & Mohammed-Baksh, 2021). The initiative and cognitive effort lie primarily with the consumer, who must sift through the "wisdom of the crowd" to find relevant cues. Conversely, chatbots embody an interactive strategy, providing real-time, personalized assistance through conversational interfaces (Yen & Chiang, 2020). The chatbot, simulating a sales assistant, can ask clarifying questions and provide tailored responses. This strategy is characterized by its dynamic, two-way communication flow.

Although both UGC and chatbots are recognized as key uncertainty reduction tools, the literature requires a direct comparison in order to assess their efficacy. Crucially, in our knowledge, no study has examined whether such strategies are interchangeable, or whether they possess particular, specialized strengths assuaging different forms of product uncertainty. This represents an important gap because UGC represents an active, consumer-driven information search, whereas chatbots offer an interactive, system-driven consultation. Drawing on URT, this study argues that these fundamental differences in nature ensure differential effectiveness across the dimensions of description, performance, and fit uncertainty. Consequently, this research provides a central theoretical contribution by systematically comparing these two dominant strategies to determine their specific roles in the consumer's journey toward a purchase decision.

This study addresses three research questions:

1. How do UGC characteristics and chatbot dimensions differentially influence various types of product uncertainty?

2. To what extent does product uncertainty reduction mediate the relationship between these strategies and purchase intention?
3. Which strategy proves more effective for specific types of product uncertainty?

By examining these questions through CB-SEM analysis, this research provides valuable insights for theoretical development and practical implementation of uncertainty reduction strategies in online retail.

The paper is structured as follows: after this introduction, we present the theoretical framework and develop our hypotheses. We then outline the methodology, present the results, and discuss the findings, their theoretical and practical implications, as well as the study's limitations and avenues for future research.

1. Theoretical Framework and Hypotheses Development

1.1. Uncertainty Reduction Theory in Online Retail

Uncertainty reflects the degree to which upcoming events cannot be accurately predicted (Ng et al., 2021; Sun et al., 2022), which varies across different contexts (Lembregts and Pandelaere, 2019). Actually, Uncertainty Reduction Theory (URT) provides the foundational framework for understanding how consumers will address information gaps in a specific context such the online shopping environments. Originally, developed to explain interpersonal communication dynamics (Berger & Calabrese, 1975), URT has been successfully applied to human-computer interaction and e-commerce contexts. Dimoka et al. (2012) first acknowledge product uncertainty as "*the buyer's difficulty in assessing the product's characteristics and predicting how the product will perform in the future*." Consumers in the digital marketplace navigate a landscape of information gaps, manifesting distinct types of product uncertainty, not only about the product descriptions and performance but also about whether the product matches their preferences and expectations (Hong and Pavlou, 2014). Description Uncertainty arises from the basic incongruence between the representation of a product and its actual reality. When sellers provide incorrect representations or withhold vital information, customers cannot verify all vital attributes, ranging from material composition to precise dimensions (Hong & Pavlou, 2010, 2014; Dimoka et al., 2012). This situation is exacerbated by inherent constraints of the online context, where the inability to physically touch, feel, or closely view an item-which places buyers at the mercy of digital content that may be incomplete or strategically selected. This type of uncertainty is most pronounced for products for which sensory attributes such as texture, finish, or heft are important in determining perceived value.

Second, Performance Uncertainty addresses questions of functionality and durability. It concerns doubts over whether a product is going to last over time, function well, and perform in the real world as it was promised to (Dimoka et al., 2012; Tan, Chandukala, & Reddy, 2022). Naturally, this dimension is interlinked with description uncertainty because a seller might either not know about the inherent quality of a product or it may be hard for him to credibly communicate and stand behind its future performance (Dimoka et al., 2012). This type of uncertainty is particularly pivotal for complex or experience-based goods, where true quality can only be gauged through actual use.

Third, Fit Uncertainty is personal because the consumer struggles to gauge whether the product fits his or her unique needs, preferences, and contexts. Fit Uncertainty goes well beyond objective specifications into subjective judgments: Will this be the right size? Does this style suit me? Will it serve my intended purpose? This uncertainty presents a major hurdle for consumers in product categories—such as apparel, cosmetics, and furniture—where personal taste and physical compatibility are paramount. Consumers find themselves mentally trying to project how an item will fit into their lives, without having the relevant cues to make that judgment confidently. The coexistence of these three dimensions presents a complex challenge to online retailers. Each type of uncertainty resonates across customer segments and product categories, suggesting the requirement for effective mitigation with tailored strategies. This nuanced understanding of uncertainty provides a critical foundation for investigating how specific digital tools-such as User-Generated Content and chatbots-can be deployed to deliver the right kind of information and interaction to each distinct consumer concern.

URT suggests that consumers actively seek information to reduce these uncertainties before making purchase decisions, making it particularly relevant for understanding how UGC and chatbots influence consumer behavior.

1.2. User-Generated Content as Active Uncertainty Reduction

(Mathur et al., 2022) recognize UGC as content created, published, and controlled by social media users based on their personal experience. UGC is characterized by uniqueness, and authenticity based on personal invention (Kumar et al., 2016; Chung, 2025). It encompasses various forms of content, including reviews, ratings, photos, and videos (Kaplan & Haenlein, 2010). UGC faithfully reports consumers' experiences with brands which transforms it into a valuable source of information. Most researchers (Al-Abdallah and Wright, 2025; Al-Abdallah and Jumaa, 2022) have adopted one or more of the following fundamental dimensions to measure content effectiveness in both UGC:

Trustworthiness refers to the perceived credibility and believability of UGC. When consumers perceive content as trustworthy, they are more likely to rely on it for uncertainty reduction across all dimensions (Racherla & Friske, 2012).

Valence represents the emotional tone and evaluative direction of UGC. Both positive and negative valence can reduce uncertainty by providing balanced perspectives on product performance and suitability (Cheong & Mohammed-Baksh, 2021).

Information Richness captures the detail, variety, and clarity of UGC content. Rich information sources like videos and detailed reviews provide comprehensive insights that address multiple uncertainty dimensions simultaneously (Zhu et al., 2020).

1.3. Chatbots as Interactive Uncertainty Reduction

Chatbots represent AI-powered conversational agents that simulate human interaction that is supported by advanced mobile technology, cloud technology, big data, and biometrics, while relying on natural language processing, such as text and semantic analyses, to generate answers (Yen & Chiang, 2020; Zumstein & Hundertmark, 2017; Huang & Rust, 2021). Chatbots are utilized in several fields as chat programs (Jiang et al., 2022). Chatbots takes different forms, such as interactive avatars (Keeling et al., 2010), animated pictures, and human-like animated agents that mimic real sales personnel (Verhagen et al., 2014), to avail an innovative interactive channel and create novel experiences. To assess the impact of the external characteristics of chatbots on consumer behavior, we conceptualize chatbots through three key dimensions established in human-computer interaction literature:

Anthropomorphism entails a tendency to impart real or imaginary non-human entities with human characteristics, motives, intentions, or emotions (Epley et al., 2007). It comprises visual cues, such as appearances or avatars; identity cues, such as gen der, name, and identity; and conversational cues, such as mimicking human languages and information interactivity (Araujo, 2018). Hence, anthropomorphism refers to the assignment of human-like characteristics to chatbots, including personality, language patterns, and emotional expression (Araujo, 2018).

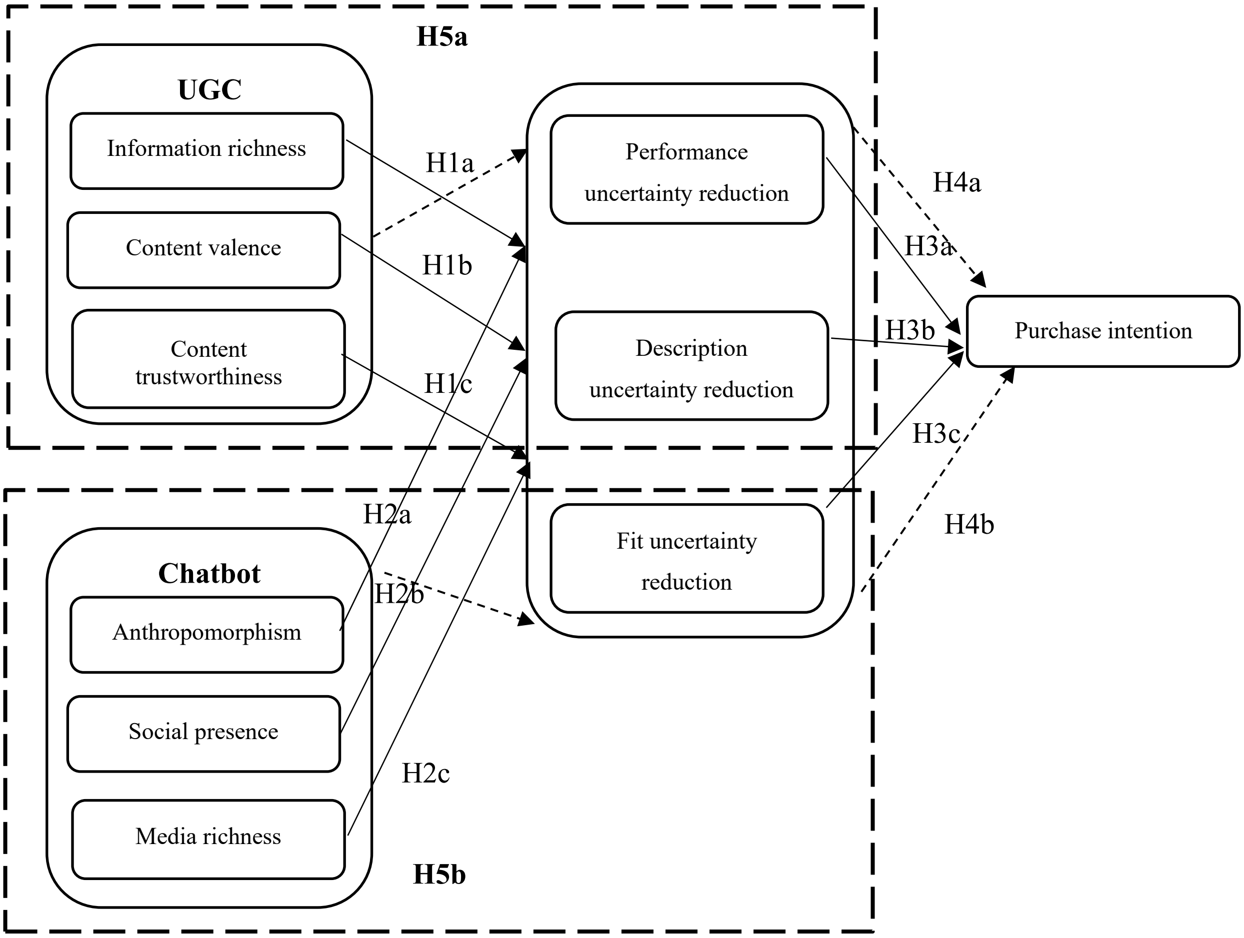
Social Presence refers to "the feeling of being with another person" (Biocca, & Harms, 2003). While, research on social presence initially considers interpersonal interactions, advancement in technology turns interest and stimulate a sense of social presence to AI technology (Van Doorn, 2016). It captures the degree to which chatbots create a sense of human contact and interpersonal connection (Araujo, 2018). For the retailer, social presence of chatbots should mainly focus on creating intimate relationships with consumers in terms of human contact, sensitivity, and warmth (Gao et al., 2018).

Media Richness theory proposes that individuals distinguish communication technologies on a scale from lean to rich based on the technology's intrinsic properties. Media richness describes the chatbot's capacity to convey multiple information cues, provide immediate feedback, and personalize communication (Daft & Lengel, 1986).

1.4. Research Model and Hypotheses

Based on the theoretical framework, we propose the following research model and hypotheses:

Fig1. Research model



UGC Effects on Product Uncertainty Reduction

User-Generated Content serves as a powerful *active* uncertainty reduction strategy, allowing consumers to proactively seek information from the collective experiences of their peers (Cheong & Mohammed-Baksh, 2021). Its perceived value is rooted in its authenticity and derivation from non-commercial sources, making it a critical resource for mitigating the three core dimensions of product uncertainty.

Trustworthiness is the cornerstone of UGC's efficacy. It refers to the perceived credibility and believability of the user-generated information (Racherla & Friske, 2012). Trustworthy UGC acts as a credible signal that directly counters the information asymmetry inherent in online transactions, where sellers may be unable or unwilling to fully disclose product limitations (Dimoka et al., 2012). When consumers perceive reviews as honest and reliable, they gain confidence in the accuracy of the seller's product descriptions, thereby reducing description uncertainty (DESC). Furthermore, credible user testimonials about a product's durability and functionality over time provide social proof of its quality, mitigating performance uncertainty

(PERF). Finally, for fit uncertainty (FIT), trustworthy UGC from users who self-report similar profiles or needs offers credible, relatable evidence about how a product might align with a new consumer's specific context, preferences, and body type, which is often absent from marketer-created content.

H1a: UGC trustworthiness positively influences description (DESC), performance (PERF), and fit (FIT) uncertainty reduction.

Valence, representing the emotional tone and evaluative direction of UGC, provides a balanced perspective that is instrumental for uncertainty reduction (Cheong & Mohammed-Baksh, 2021). A mix of positive and critical comments is particularly valuable. Overwhelmingly positive valence can reinforce performance claims, while negative reviews often highlight specific flaws or mismatches, helping consumers set realistic expectations for both product performance (PERF) and the accuracy of its description (DESC). For fit uncertainty (FIT), valence that includes detailed personal experiences (e.g., "this ran large for me," "the color was darker than pictured") is directly diagnostic. This qualitative feedback provides concrete, contextual cues that help potential buyers judge the product's alignment with their own unique tastes and requirements, going beyond objective specifications.

H1b: UGC valence positively influences DESC, PERF, and FIT uncertainty reduction.

Information-rich UGC, such as high-resolution images, detailed text, and video demonstrations, provides a multi-faceted and vivid view of the product (Zhu et al., 2020). Videos and multiple photos from various angles can reveal product details, textures, and scale that official descriptions may omit, directly reducing description uncertainty (DESC). Demonstrations of a product in use provide tangible, observable evidence of its functionality and robustness, thereby mitigating performance uncertainty (PERF). Most importantly, as highlighted by Sun et al. (2022), rich media like user-uploaded photos and videos facilitate mental imagery. This psychological process allows potential buyers to vividly imagine themselves using the product, which is a crucial mechanism for evaluating subjective and personal compatibility, thereby significantly reducing fit uncertainty (FIT).

H1c: UGC information richness positively influences DESC, PERF, and FIT uncertainty reduction.

The Influence of Chatbots on Product Uncertainty Reduction

Chatbots represent an *interactive* uncertainty reduction strategy, simulating a real-time, personalized consultation that mirrors the guidance of an in-store sales assistant (Yen & Chiang, 2020). Their strength lies in their ability to provide on-demand, tailored information through a dynamic dialogue.

Anthropomorphism, or the assignment of human-like characteristics such as a name, personality, and conversational language, enhances the user experience by fostering a sense of social connection (Araujo, 2018). This increased engagement makes users more receptive to the information provided. An anthropomorphic chatbot, perceived as a knowledgeable assistant, can encourage users to ask more detailed and probing questions about product specifications (reducing DESC uncertainty) and long-term reliability (reducing PERF uncertainty). For fit uncertainty (FIT), an anthropomorphic agent can effectively mimic the empathetic guidance of a human salesperson by asking follow-up questions to understand a user's specific needs and context, thereby delivering more personalized and convincing recommendations.

H2a: Chatbot anthropomorphism positively influences DESC, PERF, and FIT uncertainty reduction.

Social presence, defined as the "feeling of being with another" (Biocca & Harms, 2003), is critical for building trust in human-computer interaction. When a chatbot is perceived as sensitive, warm, and responsive, it creates a sense of human contact (Gao et al., 2018). This perceived warmth builds trust, making consumers more likely to believe the information it provides about product features (reducing DESC uncertainty) and performance claims (reducing PERF uncertainty). The feeling of social connection is particularly powerful for reducing fit uncertainty (FIT). As Sun et al. (2022) discuss in a related context, technologies that foster a sense of presence can make consumers more comfortable and confident in their subjective judgments about personal fit, as the interaction feels less transactional and more like a supportive consultation.

H2b: Chatbot social presence positively influences DESC, PERF, and FIT uncertainty reduction.

A chatbot's media richness—its ability to provide immediate feedback, use natural language, and share multimedia (like images or links to video demos)—directly addresses dynamic information gaps (Daft & Lengel, 1986). It can instantly clarify ambiguous product descriptions by providing supplementary visuals or detailed specifications, thereby reducing description uncertainty (DESC). It can also furnish detailed technical data or warranty information to directly assure performance (PERF). For fit uncertainty (FIT), a rich-media chatbot can engage in a level of interactive diagnosis that static UGC cannot match. For instance, it can ask for a user's room dimensions or style preference and instantly generate a personalized suggestion or visualization, effectively bridging the "last mile" of personalization.

H2c: Chatbot media richness positively influences DESC, PERF, and FIT uncertainty reduction.

Consequences of Uncertainty Reduction on Purchase Intention

Drawing from Prospect Theory (Kahneman & Tversky, 1979), consumers are inherently loss-averse and have a strong preference for certain, known outcomes over uncertain ones. The various dimensions of product uncertainty represent potent forms of perceived risk. Therefore, when these uncertainties are successfully mitigated, the perceived risk of a negative post-purchase outcome diminishes.

H3a: A reduction in description uncertainty (DESC) increases purchase intention, as consumers feel confident that the product they will receive matches its online representation.

H3b: A reduction in performance uncertainty (PERF) increases purchase intention, as consumers are assured of the product's functionality and durability.

H3c: A reduction in fit uncertainty (FIT) increases purchase intention, as consumers believe the product is well-suited to their personal needs and context.

This collective reduction in anticipated regret and financial loss directly translates into a higher willingness to proceed with the purchase.

The Mediating Role of Product Uncertainty Reduction

We posit that the influence of UGC characteristics (trustworthiness, valence, richness) and chatbot dimensions (anthropomorphism, social presence, media richness) on purchase intention is not primarily direct. Instead, their impact is fundamentally channeled through the reduction of product uncertainty. In other words, these information strategies are effective precisely because they first successfully address the specific doubts (DESC, PERF, FIT) that inhibit consumers. It is this reduction in cognitive and perceived risk that, in turn, fosters a stronger intention to buy.

H4: Product uncertainty reduction mediates the relationship between (a) UGC characteristics and purchase intention, and (b) chatbot dimensions and purchase intention.

The Comparative Effects of UGC and Chatbots

The relative effectiveness of UGC and chatbots varies across uncertainty types. The theoretical distinction between *active* (UGC) and *interactive* (chatbot) strategies suggests they are differentially effective at addressing specific uncertainty types.

UGC, as an archive of collective wisdom from a multitude of real users, is uniquely powerful for verifying objective claims. For performance uncertainty (PERF), a long-term pattern of reviews discussing real-world durability and reliability across many users is inherently more credible and diagnostic than the assurances of a seller-affiliated chatbot. Similarly, for description uncertainty (DESC), a crowd-sourced collection of user photos and videos—showing the product from every angle, in different lighting conditions, and with honest assessments of material quality—provides a level of verifiable, unbiased detail that a chatbot's programmed responses are unlikely to surpass.

H5a: UGC has a stronger effect on performance (PERF) and description (DESC) uncertainty reduction than chatbots.

Conversely, the interactive nature of chatbots is their key advantage for subjective judgments. While UGC can aid mental imagery, it is a one-way, static flow of information. Chatbots, however, enable a true *interactive* uncertainty reduction strategy. They can dynamically ask diagnostic questions to understand a user's unique needs, preferences, and context (e.g., "What is your skin type?" "What size space are you placing this in?"). This interactive process, akin to a personalized consultation in a physical store, allows chatbots to provide tailored recommendations that more effectively bridge the "last mile" of personalization. This dynamic, responsive dialogue is potentially more powerful than static UGC in creating the confidence needed to overcome the highly subjective nature of fit uncertainty (FIT).

H5b: Chatbots have a stronger effect on fit uncertainty (FIT) reduction than UGC.

2. Methodology

2.1. Research Design and Data Collection

This study employed an online survey design. Data were collected from Tunisian active online shoppers who had made at least three online purchases in the past six months and regularly consulted UGC and Chatbot before purchases. The questionnaire was distributed electronically to panel members who had opted-in to participate in academic research. A purposive sampling strategy was non-probability method employed to target respondents who were active in the e-commerce environment. Selection criteria and verification were used. To qualify for the survey, respondents had to pass a multi-stage screening process:

1. Primary Screening: Participants were required to confirm they were 18 years or older and had made at least three online purchases in the past six months.

2. Behavioral Screening (UGC & Chatbot Usage): Crucially, to ensure respondents were familiar with both uncertainty reduction strategies, they were presented with two specific screening questions:
   - *"How often do you consult user-generated content (e.g., customer reviews, user photos/videos) before making an online purchase?"*
   - *"How often do you use a live chat or chatbot on a retail website to ask questions about a product before purchasing?"*

     Only respondents who selected "Often" or "Always" for *both* questions were permitted to proceed with the main survey. This step directly verified the core behavioral criterion of regularly consulting both UGC and chatbots.

After applying these filters and removing incomplete responses and those failing attention checks, the final sample consisted of 455 valid responses from 600 initial participants, yielding a 75.8% valid response rate. Participants represented major product categories: electronics (35%), apparel (30%), home goods (20%), and other retail products (15%).

Table 1: Demographic Profile of Respondents (N=455)

Demographic Characteristic	Category	Frequency	Percentage (%)
Gender	Male	238	52.3%
	Female	217	47.7%
Age	18-24	114	25.1%
	25-34	182	40.0%
	35-44	102	22.4%
	45+	57	12.5%
Education Level	High School or less	68	14.9%
	Bachelor's Degree	273	60.0%
	Master's Degree or higher	114	25.1%
Monthly Online Shopping Frequency	3-4 times	265	58.2%
	5-6 times	136	29.9%
	More than 6 times	54	11.9%
Product Category of Last Purchase	Electronics	159	35.0%
	Apparel & Fashion	137	30.1%

	Home & Living Goods	91	20.0%
	Other Retail Products	68	14.9%

2.2. Measurement Instruments

All constructs were measured using reflective scales adapted from established literature on 5-point Likert scales (1 = Strongly Disagree to 5 = Strongly Agree).

UGC is assessed through Trustworthiness (4 items adapted from Racherla & Friske, 2012), Valence (3 items adapted from Cheong & Mohammed-Baksh, 2021) and Information Richness (4 items adapted from Zhu et al., 2020). Trustworthiness translates credibility and honesty. Valence evaluates positive impressions. Information Richness measures comprehensiveness.

Chatbot dimensions encompasses: Anthropomorphism (5 items), Social Presence (4 items) and Media Richness (4 items), adapted from Yen & Chiang (2020). Anthropomorphism assesses human-like qualities. Social Presence measures human contact perception. Media richness evaluates communication quality.

Product Uncertainty Reduction was adapted from Dimoka et al. (2012), and assessed using: Description Uncertainty Reduction (3 items), Performance Uncertainty Reduction (3 items), Fit Uncertainty Reduction (3 items)

Purchase Intention was measured with 4 items adapted from Hutter et al., (2013)

2.3. Data Analysis Strategy

We employed Covariance-Based Structural Equation Modeling (CB-SEM) using AMOS 23.0 for hypothesis testing. The analysis followed a two-step approach: first assessing the measurement model, then testing structural relationships. Measurement model assessment included confirmatory factor analysis, composite reliability, average variance extracted, and discriminant validity tests.

3. Results

3.1. Measurement Model Assessment

The measurement model demonstrated excellent psychometric properties. All factor loadings exceeded 0.70, with AVE values ranging from 0.62 to 0.71, above the 0.50 threshold. Composite reliability scores ranged from 0.87 to 0.93, and Cronbach's alpha values ranged between 0.86 and 0.91, indicating strong internal consistency. Discriminant validity was established via the Fornell-Larcker criterion and HTMT ratios.

Table 2: Measurement Model Assessment (Factor Loadings, Reliability, and Validity)

Construct and Indicators	Factor Loading	Cronbach's Alpha (α)	CR	AVE
UGC Trustworthiness		**0.89**	**0.91**	**0.67**
The user reviews for this product are trustworthy.	0.82			
The user reviews for this product are credible.	0.84			
The user reviews for this product are reliable.	0.81			
The user reviews for this product are honest.	0.79			
UGC Valence		**0.86**	**0.90**	**0.70**
The user reviews for this product are generally positive.	0.85			
The user reviews for this product are favorable.	0.83			
The user reviews for this product convey a good impression.	0.83			
UGC Information Richness		**0.90**	**0.92**	**0.71**
The user-generated content (e.g., photos, videos, text) for this product provides a wealth of relevant information.	0.84			
The user-generated content for this product provides all the necessary information I need.	0.86			
The user-generated content for this product is comprehensive.	0.83			
The user-generated content for this product provides detailed information.	0.84			
Chatbot Anthropomorphism		**0.91**	**0.93**	**0.69**
Chatbot is natural.	0.82			
Chatbot is human-like.	0.85			
Chatbot is polite	0.83			
Chatbot is authentic.	0.81			
Chatbot is realistic.	0.84			
Chatbot Social Presence		**0.88**	**0.91**	**0.68**
There is a sense of human contact when I communicate with conversational agent.	0.83			
There is a sense of sociability.	0.82			
There is a sense of human warmth.	0.84			

There is a sense of human sensitivity.	0.81			
Chatbot Media Richness		**0.87**	**0.90**	**0.62**
Chatbot can handle multiple information cues simultaneously.	0.80			
Chatbot can facilitate rapid feedback.	0.78			
Chatbot can establish a personal focus.	0.79			
Chatbot message can be explicitly expressed or easy to be comprehend.	0.78			
Description Uncertainty Reduction		**0.87**	**0.91**	**0.70**
The information available gives me a very good idea of the product's description.	0.84			
I feel very confident that I know what the product is like.	0.85			
I can very accurately assess the product's attributes.	0.82			
Performance Uncertainty Reduction		**0.88**	**0.92**	**0.71**
The information available gives me a very good idea of the product's performance.	0.85			
I feel very confident that I know how well the product will perform.	0.86			
I can very accurately assess the product's quality and durability.	0.83			
Fit Uncertainty Reduction		**0.89**	**0.92**	**0.70**
The information available gives me a very good idea of how the product fits my needs.	0.84			
I feel very confident that the product is a good match for me.	0.86			
I can very accurately assess if the product is right for someone like me.	0.83			
Purchase Intention		**0.90**	**0.92**	**0.69**
I am likely to purchase this product based on these information sources, in the near future.	0.83			
I will consider buying this product based on these information sources, the next time I need a product like this.	0.85			
The probability that I will consider buying this product based on these information sources is high.	0.82			
I am willing to purchase this product based on these information sources.	0.82			

Note: All factor loadings are significant at $p < 0.001$.

Table 3: Discriminant Validity - Fornell-Larcker Criterion

Construct	1	2	3	4	5	6	7	8	9	10
1. UGC Trustworthiness	**0.82**									
2. UGC Valence	0.45	**0.84**								
3. UGC Information Richness	0.51	0.48	**0.84**							
4. Chatbot Anthropomorphism	0.32	0.29	0.35	**0.83**						
5. Chatbot Social Presence	0.38	0.31	0.40	0.58	**0.82**					
6. Chatbot Media Richness	0.29	0.25	0.47	0.52	0.49	**0.79**				
7. Desc. Uncertainty Reduction	0.53	0.49	0.61	0.41	0.45	0.38	**0.84**			
8. Perf. Uncertainty Reduction	0.55	0.51	0.59	0.38	0.43	0.35	0.62	**0.84**		
9. Fit Uncertainty Reduction	0.57	0.58	0.52	0.50	0.53	0.46	0.58	0.61	**0.84**	
10. Purchase Intention	0.49	0.47	0.55	0.44	0.48	0.41	0.59	0.62	0.66	**0.83**

To assess the potential for common method bias, Harman's single-factor test was performed. The unrotated factor solution revealed that the first factor accounted for 32.8% of the variance, which is below the 50% threshold, suggesting that common method bias is not a major concern in this dataset.

3.2.Structural Model and Hypothesis Testing

The structural model demonstrated good fit: $\chi^2/df = 2.28$, CFI = 0.94, TLI = 0.93, RMSEA = 0.05. The model explained substantial variance in both product uncertainty reduction (R^2 = 0.68, SRMR = 0.04) and purchase intention (R^2 = 0.59).

Table 4: Structural Path Coefficients and Hypothesis Testing

Hypothesis	Path	Std. Estimate (β)	p-value	Result
H1a_P	UGC Trust → Performance UR	0.29	<0.001	Supported
H1b_P	UGC Valence → Performance UR	0.25	<0.001	Supported
H1c_P	UGC Richness → Performance UR	0.38	<0.001	Supported
H1a_D	UGC Trust → Description UR	0.27	<0.001	Supported
H1b_D	UGC Valence → Description UR	0.23	0.002	Supported
H1c_D	UGC Richness → Description UR	0.42	<0.001	Supported

H1a_F	UGC Trust → Fit UR	0.31	<0.001	Supported
H1b_F	UGC Valence → Fit UR	0.35	<0.001	Supported
H1c_F	UGC Richness → Fit UR	0.26	<0.001	Supported
H2a_P	Chatbot AN → Performance UR	0.18	0.003	Supported
H2b_P	Chatbot SP → Performance UR	0.22	<0.001	Supported
H2c_P	Chatbot MR → Performance UR	0.09	0.105	Not Supported
H2a_D	Chatbot AN → Description UR	0.16	0.008	Supported
H2b_D	Chatbot SP → Description UR	0.19	0.002	Supported
H2c_D	Chatbot MR → Description UR	0.11	0.065	Not Supported
H2a_F	Chatbot AN → Fit UR	0.27	<0.001	Supported
H2b_F	Chatbot SP → Fit UR	0.28	<0.001	Supported
H2c_F	Chatbot MR → Fit UR	0.21	<0.001	Supported
H3a	Performance UR → Purchase Intention	0.28	<0.001	Supported
H3b	Description UR → Purchase Intention	0.25	<0.001	Supported
H3c	Fit UR → Purchase Intention	0.32	<0.001	Supported

P: Performance Uncertainty; D: Description Uncertainty; F: Fit Uncertainty; UR: Uncertainty Reduction; AN: Anthropomorphism; SP: Social Presence; MR: Media Richness

The path analysis, summarized in Table 4, yielded several key findings. First, all characteristics of User-Generated Content (trustworthiness, valence, and information richness) demonstrated strong and statistically significant positive effects on reducing all three types of product uncertainty (description, performance, and fit), confirming their robust role as an active uncertainty reduction strategy. Second, the effects of chatbot dimensions were more nuanced; while anthropomorphism and social presence significantly reduced all uncertainty types, media richness failed to significantly reduce performance ($\beta = 0.09$, $p = 0.105$) and description uncertainty ($\beta = 0.11$, $p = 0.065$). Third, in line with the comparative hypothesis, chatbots showed their strongest influence on fit uncertainty reduction, with anthropomorphism ($\beta = 0.27$) and social presence ($\beta = 0.28$) being particularly potent predictors. Finally, the reduction of all three uncertainty types significantly increased purchase intention, with fit uncertainty reduction exhibiting the strongest effect ($\beta = 0.32$).

To determine the nature of mediation (full vs. partial), we followed the procedure recommended by Zhao et al. (2010). We first tested a model including direct paths from UGC characteristics and chatbot dimensions to purchase intention. The results showed that for UGC paths, all direct effects were non-significant ($p > 0.05$), confirming full mediation. For chatbots, some paths showed significant direct effects alongside significant indirect effects, indicating partial mediation. The specific mediation type for each path is detailed in Table 5.

Table 5: Complete Mediation Analysis Results

Hypothesis	Mediation Path	Std. Indirect Estimate	95% Bias-Corrected CI	Std. direct Estimate	p-value	Result	Mediation type
H4a	UGC Trust → Performance UR → PI	0.08	[0.04, 0.13]	0.02	<0.001	Supported	Full mediation
	UGC Valence → Performance UR → PI	0.07	[0.03, 0.11]	0.03	<0.001	Supported	Full mediation
	UGC Richness → Performance UR → PI	0.11	[0.06, 0.16]	0.04	<0.001	Supported	Full mediation
	UGC Trust → Description UR → PI	0.07	[0.03, 0.11]	0.01	<0.001	Supported	Full mediation
	UGC Valence → Description UR → PI	0.06	[0.02, 0.10]	0.02	<0.001	Supported	Full mediation
	UGC Richness → Description UR → PI	0.11	[0.06, 0.15]	0.05	<0.001	Supported	Full mediation
	UGC Trust → Fit UR → PI	0.10	[0.05, 0.15]	0.03	<0.001	Supported	Full mediation
	UGC Valence → Fit UR → PI	0.11	[0.06, 0.16]	0.02	<0.001	Supported	Full mediation
	UGC Richness → Fit UR → PI	0.08	[0.04, 0.13]	0.04	<0.001	Supported	Full mediation
H4b	Chatbot AN → Performance UR → PI	0.05	[0.02, 0.09]	0.08	0.004	Supported	Partial mediation
	Chatbot SP → Performance UR → PI	0.06	[0.03, 0.10]	0.09	<0.001	Supported	Partial mediation
	Chatbot MR → Performance UR → PI	0.03	[-0.01, 0.06]	0.06	0.120	Not Supported	No mediation

	Chatbot AN → Description UR → PI	0.04	[0.01, 0.07]	0.02	0.009	Supported	Full mediation
	Chatbot SP → Description UR → PI	0.05	[0.02, 0.08]	0.08	0.003	Supported	Partial mediation
	Chatbot MR → Description UR → PI	0.03	[-0.01, 0.06]	0.05	0.070	Not Supported	No mediation
	Chatbot AN → Fit UR → PI	0.09	[0.05, 0.13]	0.06	<0.001	Supported	Full mediation
	Chatbot SP → Fit UR → PI	0.09	[0.05, 0.14]	0.07	<0.001	Supported	Full mediation
	Chatbot MR → Fit UR → PI	0.07	[0.03, 0.11]	0.04	<0.001	Supported	Full mediation

P: Performance Uncertainty; D: Description Uncertainty; F: Fit Uncertainty; UR: Uncertainty Reduction; AN: Anthropomorphism; SP: Social Presence; MR: Media Richness

4. Discussion

This study delivers a nuanced comparative analysis of two dominant uncertainty reduction strategies in online retail. By positioning User-Generated Content (UGC) as an active strategy and chatbots as an interactive strategy, and by dissecting product uncertainty into its three core dimensions, our findings provide a more detailed understanding of how different digital tools assuage specific consumer concerns. The results significantly confirm our theoretical framework and also reveal critical boundary conditions, thereby extending the work of foundational scholars such as Dimoka et al. (2012), Hong & Pavlou (2014), and Yen & Chiang (2021).

UGC as a Comprehensive Active Strategy: The Power of Collective Verification

The first key finding of this research dwells on UGC which functions as a comprehensive uncertainty reduction tool, with all three of its characteristics—trustworthiness, valence, and information richness—significantly reducing all forms of product uncertainty. This robust, multi-faceted efficacy strongly supports UGC's role as a powerful active uncertainty reduction strategy, as conceptualized by Cheong & Mohammed-Baksh (2021).

Most notably, the deep impact of information richness on performance ($\beta=0.38$) and description ($\beta=0.42$) uncertainty directly amplifies the arguments of Dimoka et al. (2012), who entails that product uncertainty stems from an inability to assess characteristics and predict performance. Our findings demonstrate that rich UGC, such as user videos and detailed images, serves as a functional alternative for physical inspection. A video demonstrating a product's use provides tangible evidence of its functionality, directly mitigating performance uncertainty, while high-resolution photos from multiple angles reveal texture and scale, directly countering description uncertainty. This is in line with Zhu et al. (2020), yet we extend their work by quantitatively showing that richness is not just about perceived information quality but is a primary driver of specific uncertainty reduction.

Furthermore, the significant role of trustworthiness across all uncertainty types underlines the importance of source credibility, as emphasized by Racherla & Friske (2012). In the context of Hong & Pavlou's (2014) model of information asymmetry, trustworthy UGC acts as a credible signal that bypasses the seller's potential incentive to withhold negative information. Our results approve that peer credibility is the bedrock upon which uncertainty reduction is built, whether for verifying objective facts (description, performance) or subjective suitability (fit).

The Specialized Niche of Chatbots: Excelling at Social and Interactive Fit

The results for chatbots reveal a more specialized profile, refining our understanding of their utility in e-commerce. The strong, significant effects of anthropomorphism and social presence on fit uncertainty reduction (β=0.27 and β=0.28, respectively) provide robust empirical support for the arguments of Araujo (2018) and Yen & Chiang (2021). These scholars posited that human-like and socially present chatbots could mimic the empathetic guidance of in-store assistants. Our study confirms this, demonstrating that these social cues are not merely about user enjoyment but are functionally critical for resolving the highly personal dilemma of "whether this product is right for me." The interactive dialogue allows the chatbot to perform a diagnostic role—asking for a user's skin type, room dimensions, or style preference—that static UGC cannot replicate. This finding directly addresses the core of fit uncertainty as defined by Hong & Pavlou (2014), showing that interactive, personalized consultation is its most potent antidote.

However, the same social dimensions (anthropomorphism, social presence) revealed weaker effects on description and performance uncertainty. This suggests a friendly and human-like chatbot does not inherently make it a more credible source for technical data. This nuances the findings of Van Doorn (2016) on social presence in human-computer interaction field, indicating that its benefits are context-dependent and most potent for subjective, personal judgments.

The Critical Limitation of Chatbot Media Richness and a Theoretical Reconciliation

Maybe the most telling finding is the non-significant effect of chatbot media richness on performance and description uncertainty. This appears to contradict Media Richness Theory

(Daft & Lengel, 1986), which would predict that a rich medium like a chatbot should be effective for resolving ambiguous issues. However, this contradiction is only superficial. Our results suggest a crucial theoretical refinement: a medium's richness (its capacity to convey multiple cues) is distinct from its credibility (its perceived trustworthiness as an information source).

While a chatbot can provide rich, immediate information, it remains a single, retailer-affiliated entity. In contrast, UGC represents the aggregated, often contradictory, "wisdom of the crowd." For verifying objective claims about performance and description, consumers seem to trust the collective, disconfirmation-prone evidence of UGC more than the pre-programmed responses of a chatbot, no matter how rich the medium. This finding critically extends Dimoka et al.'s (2012) work on product uncertainty by introducing a "source credibility" layer to media selection. It suggests that for tasks requiring verification, the crowd-sourced, active strategy of UGC is superior to the interactive, but single-source, strategy of a chatbot.

The Mediating Pathway and Comparative Theoretical Implications

The mediation analysis (H4) strengthens the central pathway of our model. In fact, the influence of both UGC and chatbots on purchase intention is fundamentally channeled through the reduction of product uncertainty. This fully aligns with the core tenet of Uncertainty Reduction Theory (Berger & Calabrese, 1975) and its application in e-commerce by Featherman & Pavlou (2003). It confirms that these tools are effective precisely because they first resolve the fundamental cognitive barriers—the uncertainties—that inhibit the purchase decision.

The comparative hypotheses (H5a, H5b) were strongly supported, and this is the core of our theoretical contribution. We empirically validate the conceptual distinction between active and interactive uncertainty reduction strategies. UGC's superiority for performance and description uncertainty underscores its role as a verification engine, leveraging collective intelligence to confirm objective claims. Conversely, the chatbot's superiority for fit uncertainty highlights its role as a personalization engine, using interaction to bridge the subjective gap between the product and the consumer's self-concept. This finding directly answers the call by Sun et al. (2022) for research on technologies that aid mental imagery and fit assessment, demonstrating that interactive conversation is more powerful than static content for this specific task.

Practical Implications

The findings lead to a clear, strategic imperative for online retailers: implement a division of labor between UGC and chatbots.

For high-performance/description uncertainty products (electronics, appliances), Amazon provides an excellent example of platform which prioritizes and curates UGC. Online retail managers should develop programs that incentivize detailed, information-rich reviews with videos and photos. The chatbot on these pages should be designed to direct users to this UGC (e.g., "I can show you the most helpful reviews with videos") rather than attempting to answer technical queries itself.

For high-fit uncertainty products (apparel, cosmetics, furniture), online retail managers may invest in chatbots with advanced anthropomorphism and social presence. Their primary function should be interactive diagnosis—asking a series of questions to understand personal needs and then providing a tailored, confident recommendation. UGC remains important here, but the chatbot should be the star of the show, guiding the personal fit decision.

Conclusion

This research demonstrates that both User-Generated Content and chatbots effectively reduce product uncertainty in online retail, but through distinct mechanisms and with differential impacts across uncertainty dimensions. UGC serves as a powerful active strategy for addressing performance and description uncertainties through rich, user-driven content. Chatbots function as effective interactive strategies for resolving fit uncertainty through social presence and anthropomorphism.

The findings provide a nuanced understanding of how these strategies complement each other in the consumer decision process. For online retailers, the strategic implication is clear: a balanced approach that leverages UGC for technical information and chatbots for personal guidance is likely to be most effective in reducing consumer uncertainty and driving purchase decisions.

As online retail continues to evolve, the strategic integration of both active and interactive uncertainty reduction strategies will be crucial for creating satisfying consumer experiences that drive purchase completion and long-term loyalty.

Limitations and Future Research

Several limitations suggest directions for future research. First, the cross-sectional design prevents causal inferences about the relationships examined. Longitudinal studies tracking uncertainty reduction over time would strengthen causal claims.

Second, while the sample represented major product categories, future research could examine category-specific and product type effects more systematically. Different products might exhibit distinct uncertainty reduction patterns based on their complexity, price, and purchase frequency.

Third, cultural factors might moderate the effectiveness of different uncertainty reduction strategies. Cross-cultural comparisons could reveal interesting variations in strategy preferences and effectiveness.

Finally, future research could explore the integration of UGC and chatbots more deeply, examining how these strategies can be combined to create more comprehensive uncertainty reduction systems.

REFERENCES

Al-Abdallah, G., & Jumaa, M. (2022). The impact of electronic word-of-mouth on consumer purchase intention. *Journal of Marketing Communications*, 28(4), 345-362.

Al-Abdallah, G., & Wright, L. T. (2025). User-generated content and brand trust: A cross-cultural analysis. *Journal of Consumer Behaviour*, 24(1), 112-128.

Araujo, T. (2018). Living up to the chatbot hype: The influence of anthropomorphic design cues and communicative agency framing on conversational agent and company perceptions. *Computers in Human Behavior*, 85, 183-189.

Berger, C. R., & Calabrese, R. J. (1975). Some explorations in initial interaction and beyond. *Human Communication Research*, 1(1), 99-112.

Biocca, F., & Harms, C. (2003). *A guide to the revised networked minds social presence measure*. East Lansing, MI: Michigan State University.

Cheong, H. J., & Mohammed-Baksh, S. (2021). Purchase situations and information-seeking in brand-related user-generated content. *Journal of Promotion Management*, 27(5), 740-764.

Chung, M. (2025). The authenticity paradox in user-generated content. *Journal of Interactive Marketing*, 59, 55-70.

Daft, R. L., & Lengel, R. H. (1986). Organizational information requirements, media richness and structural design. *Management Science*, 32(5), 554-571.

Dimoka, A., Hong, Y., & Pavlou, P. A. (2012). On product uncertainty in online markets. *MIS Quarterly*, 36(2), 395-426.

Epley, N., Waytz, A., & Cacioppo, J. T. (2007). On seeing human: A three-factor theory of anthropomorphism. *Psychological Review*, 114(4), 864–886.

Featherman, M. S., & Pavlou, P. A. (2003). Predicting e-services adoption. *International Journal of Human-Computer Studies*, 59(4), 451-474.

Gao, L., Liu, Y., & Wang, Z. (2018). The role of social presence in building trust in online shopping. *Journal of Electronic Commerce Research*, 19(3), 195-210.

Hong, Y., & Pavlou, P. A. (2010). *Product fit uncertainty in online markets: Nature, effects, and antecedents*. Proceedings of the International Conference on Information Systems.

Hong, Y., & Pavlou, P. A. (2014). Product fit uncertainty in online markets: Nature, effects, and antecedents. *Information Systems Research*, 25(2), 328-344.

Huang, M. H., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. *Journal of the Academy of Marketing Science*, 49(1), 30–50.

Hutter, K., Hautz, J., Dennhardt, S., & Fuller, J. (2013). The impact of user interactions in social media on brand awareness and purchase intention. *Journal of Product & Brand Management*, 22(5/6), 342-351.

Jiang, J., Yang, L., & Wang, E. (2022). The future of service: How AI-powered chatbots are reshaping customer interactions. *Service Industries Journal*, 42(9-10), 727-749.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, 47(2), 263–291.

Kaplan, A. M., & Haenlein, M. (2010). Users of the world, unite! The challenges and opportunities of Social Media. *Business Horizons*, 53(1), 59-68.

Keeling, K., McGoldrick, P., & Beatty, S. (2010). Avatars as salespeople: Communication style, trust, and intentions. *Journal of Business Research*, 63(8), 793-800.

Kim, Y., & Krishnan, R. (2015). On product-level uncertainty and online purchase behavior: An empirical analysis. *Management Science*, 61(10), 2449-2467.

Kumar, A., Bezawada, R., Rishika, R., Janakiraman, R., & Kannan, P. K. (2016). From social to sale: The effects of firm-generated content in social media on customer behavior. *Journal of marketing*, *80*(1), 7-25.

Lembregts, C., & Pandelaere, M. (2019). Falling back on numbers: When preference for numerical product information increases after a personal control threat. *Journal of Marketing Research*, *56*(1), 104-122.

Lembregts, C., & Pandelaere, M. (2019). The role of uncertainty in the evaluation of experiences. *Journal of Consumer Research*, 46(4), 725-743.

Mathur, S., Tewari, A., & Singh, A. (2022). Modeling the factors affecting online purchase intention: the mediating effect of consumer's attitude towards user-generated content. *Journal of Marketing Communications*, *28*(7), 725-744.

Ng, S., Faraji-Rad, A., & Batra, R. (2021). Uncertainty evokes consumers' preference for brands incongruent with their global–local citizenship identity. *Journal of Marketing Research*, *58*(2), 400-415.

Racherla, P., & Friske, W. (2012). Perceived 'usefulness' of online consumer reviews. *Electronic Commerce Research and Applications*, 11(6), 548-559.

Sun, C., Fang, Y., Kong, M., Chen, X., & Liu, Y. (2022). Influence of augmented reality product display on consumers' product attitudes: A product uncertainty reduction perspective. *Journal of Retailing and Consumer Services*, *64*, 102828.

Tan, Y. C., Chandukala, S. R., & Reddy, S. K. (2022). Augmented reality in retail and its impact on sales. *Journal of marketing*, *86*(1), 48-66.

Lin, X., Featherman, M., Brooks, S. L., & Hajli, N. (2019). Exploring gender differences in online consumer purchase decision making: An online product presentation perspective. *Information Systems Frontiers*, *21*(5), 1187-1201.

Van Doorn, J. (2016). The role of social presence in human-robot interaction. *Journal of Service Research*, 19(4), 1-15.

Verhagen, T., Van Nes, J., Feldberg, F., & Van Dolen, W. (2014). Virtual customer service agents: Using social presence and personalization to shape online service encounters. *Journal of Computer-Mediated Communication*, 19(3), 529-545.

Wang, S., Ye, Y., Ning, B., Cheah, J. H., & Lim, X. J. (2022). Why do some consumers still prefer in-store shopping? An exploration of online shopping cart abandonment behavior. *Frontiers in Psychology*, *12*, 829696.

Yen, C., & Chiang, M. C. (2021). Trust me, if you can: a study on the factors that influence consumers' purchase intention triggered by chatbots based on brain image evidence and self-reported assessments. *Behaviour & Information Technology*, *40*(11), 1177-1194.

Zhu, L., Li, H., He, W., & Hong, C. (2020). What influences online reviews' perceived information quality? Perspectives on information richness, emotional polarity and product type. *The Electronic Library*, 38(2), 273-296.

Zumstein, D., & Hundertmark, S. (2017). Chatbots-An interactive technology for personalized communication and transaction. *International Journal of Advanced Science and Technology*, 102, 1-12.