Journal of Business Research 180 (2024) 114737

Contents lists available at ScienceDirect

Journal of Business Research

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

Enhancing trust in online grocery shopping through generative AI chatbots

Debarun Chakraborty[a], Arpan Kumar Kar[b], Smruti Patre[a], Shivam Gupta[c,*]

[a] Symbiosis Institute of Business Management Nagpur, Constituent of Symbiosis, International (Deemed University), Pune, India
[b] Department of Management Studies, Indian Institute of Technology Delhi, Hauz Khas, New Delhi, India
[c] Department of Information Systems, Supply Chain Management & Decision Support, NEOMA Business School, Reims, France

ARTICLE INFO

Keywords:
Generative Artificial Intelligence (AI)
Online Shopping
Elaboration Likelihood Model
Trust
Status Quo Bias Theory
Chatbots

ABSTRACT

Generative Artificial Intelligence (GAI) is witnessing a lot of adoption across industries, but literature is yet to fully document the nuances of these applications. We develop a comprehensive framework for understanding the factors that affect trust in online grocery shopping (OGS) using GAI chatbots. Our exploratory study was conducted via interviews, which helped to build our model. We integrate the Elaboration Likelihood Model (ELM) and Status Quo Bias (SQB) theory to develop the Unified Framework for Trust on Technology Platforms. In our confirmatory study, by analyzing 372 responses from users, using structural equation modelling (SEM), we initially validate our path model. Subsequently, we used fuzzy set qualitative comparative analysis (fsQCA) to check the causal combinations to explain different trust levels. Apart from perceived regret avoidance, all of the other factors had a significant effect on attitude and trust. Perceived anthropomorphism moderated the associations between interaction quality, credibility, threat, and attitude.

1. Introduction

Generative AI chatbots transform the online grocery shopping (OGS) experience by aiding clients in locating specific products, proposing substitutes, and even providing recipe suggestions tailored to their interests (Wamba, Queiroz, Jabbour, & Shi, 2023). These chatbots are seamlessly incorporated into platforms, improving the purchasing experience by saving time and providing unique recommendations for each customer (Chen, Le, & Florence, 2021). Integrating generative AI (GAI) chatbots in OGS leverages AI and natural language processing (NLP) for personalized, interactive customer experiences, meeting evolving demands and expectations (Kushwaha et al., 2021; Wamba et al., 2023). NLP is an essential element of GAI, serving a pivotal function in facilitating machines to comprehend, interpret, and produce text that resembles human language (Kar, Varsha, & Rajan, 2023). NLP techniques are utilized in GAI applications to examine and understand extensive text collections (Kushwaha et al., 2021). This enables machines to acquire knowledge about linguistic patterns, semantic interpretations, and syntactic arrangements (Wamba et al., 2023). NLP algorithms play a crucial role in creative applications, such as text generation models (Palivela, 2021). Integrating NLP into GAI improves machines' capacity to imitate human language and communication (Kar et al., 2023). This advancement enables a diverse array of applications in several industries, including customer assistance and content creation. In an era characterized by the continuous adoption of new technologies aimed at enhancing efficiency and convenience, GAI chatbots have swiftly emerged as a resounding success (Prasad Agrawal, 2023; Stahl & Eke, 2024).

GAI chatbots in OGS have the potential to enhance the shopping process by assisting users in product selection, order placement and addressing queries, ultimately contributing to increased user satisfaction and loyalty in the OGS domain. Existing literature indicates that interacting with GAI chatbots (Dwivedi et al., 2023; Harms, White, & Fezzey, 2024) is generally considered convenient, enjoyable and efficient, and this positive interaction improves consumers' perceived anthropomorphism while fostering a favorable attitude toward the system (Alimamy & Kuhail, 2023; Bawack, Wamba, & Carillo, 2021). It is predicted that by the year 2024, the use of chatbots will reach a staggering 8.4 billion units, surpassing the global human population (Statista, 2022). The adoption of GAI has enhanced these chatbots' ability to address queries that may have both factual as well as judgmental knowledge involved—and, therefore, challenges surrounding the veracity of query resolution are often evidenced (Kar et al., 2023; Sun, Chen, & Sundar, 2024). As such, it becomes necessary to comprehend the factors that contribute to building trust in OGS using GAI chatbots (Singh, 2022) due to their significant impact on repurchase intentions and overall success

* Corresponding author.
E-mail addresses: smruti.patre@sibmnagpur.edu.in (S. Patre), shivam.gupta@neoma-bs.fr (S. Gupta).

https://doi.org/10.1016/j.jbusres.2024.114737
Received 3 December 2023; Received in revised form 15 May 2024; Accepted 19 May 2024
Available online 24 May 2024
0148-2963/

in OGS platforms.

The discussion over trust in online shopping, specifically in relation to GAI chatbots, has become extremely important in today's digital environment (Kar et al., 2023). The incorporation of AI chatbots brings a transformational factor as consumers increasingly depend on e-commerce platforms for their daily needs (Sun et al., 2024). Scholars find value in deciphering the intricacies of how people perceive and place confidence in AI-powered shopping assistants, thereby enhancing overall comprehension of human behavior in the digital era (McLean, Osei-Frimpong, & Barhorst, 2021). The practical implications for practitioners are significant, ranging from creating interfaces that are transparent and user-friendly to adopting strong security measures (Gangwar, Date, & Ramaswamy, 2015). By employing GAI chatbots, trust in online buying can be improved, leading to increased consumer happiness and loyalty (Sohn, Sung, Koo, & Kwon, 2020).

However, because trust in these digital platforms facilitates better usage experience and subsequent adoption (Pavlou & Fygenson, 2006; Benbasat, Gefen, & Pavlou, 2008; Kar, 2021), it is necessary to conduct thorough research into the precise elements that influence user trust in AI chatbot suggestions (Yen & Chiang, 2021). This includes examining the role of algorithm transparency, the user's comprehension of AI processes, and the effect of personalized recommendations on establishing trust (Shin, 2020). Further investigation could explore the variances in trust dynamics across different cultures, because cultural subtleties may influence users' interpretations of AI technologies in distinct ways (Yang & Wibowo, 2022).

Current scholarship is lacking in comprehension of the lasting impacts of AI-driven interactions on user trust. Furthermore, there is a lack of research on the ethical implications linked to AI chatbot interactions, encompassing concerns of privacy, bias, and the conscientious handling of consumer data. It is essential to address these areas of research in order to create comprehensive methods that enhance confidence in online buying while guaranteeing the ethical and sustainable incorporation of GAI chatbots into OGS platforms. Hence, this study focuses on exploring the role of different factors that influence trust in OGS using GAI chatbots that attempt to demonstrate human-like interaction in online environments, are always available, and can quickly resolve most customer queries. The interplay between trust, attitudes, and technology adoption underscores the importance of delving into the factors underpinning the establishment of trust in the virtual shopping realm (Hand, Dall'Olmo Riley, Harris, Singh, & Rettie, 2009).

In response, this study offers a fresh perspective on trust in OGS using GAI chatbots by investigating the factors influencing it. Although previous studies have examined several fields in OGS (Singh & Söderlund, 2020), a substantial research gap exists surrounding trust in OGS using GAI chatbots. To narrow that gap, this study aims to establish a more comprehensive framework for understanding factors affecting trust in OGS using GAI chatbots. It is crucial to understand how the quality of interaction between users with IVA, as well as the credibility that the user ascribes to OGS using GAI chatbots, matters in developing trust. Similarly, it is equally vital to comprehend the factors that impede the development of trust in OGS. Additionally, the human-like attributes of GAI chatbots, referred to as "anthropomorphism," can either facilitate or hinder the establishment of trust in OGS when utilizing GAI chatbots. Therefore, this study investigates the role of anthropomorphism as a moderator in that context.

Through the integration of the Elaboration Likelihood Model (ELM) and Status Quo Bias (SQB) theory, we have proposed a new model, the "Unified Framework for Trust on Technology Platforms" (UFTTP), to explain out how enablers and barriers affect users' attitude and trust toward OGS using GAI chatbots. ELM has been adopted because it explains the role of central cues, which affect deep cognitive processing to influence attitude change, along with peripheral cues which can facilitate attitude change with minimal mental exertion (Aghakhani, Oh, Gregg, & Karimi, 2021). Furthermore, SQB theory explains how the utilization of features of information systems can hinder their adoption and subsequent continued usage (Kim & Kankanhalli, 2009). Given the increasing use of technology platforms and GAI chatbots, we expect that UFTTP will help future research to explain various attributes of users' behavior and how they trust these digital platforms. Our endeavor is guided by the following research questions:

RQ 1: How do interaction quality, credibility of generative AI chatbots, inertia, perceived inertia, perceived threat, and perceived regret avoidance collectively influence individuals' attitudes toward online grocery shopping using generative AI chatbots?

RQ 2: To what extent does perceived anthropomorphism moderate the impact of each independent variable on attitude toward using generative AI chatbots?

The remaining study is structured as follows. The next part provides an analysis of the theoretical framework that supports the relationship between enablers, barriers, attitudes and consumers' trust toward GAI chatbots in the context of OGS. Next, a proposed research model is presented, elucidating the hypothesized relationships. The research methodology encompasses the explicit delineation of the research instrument, participants, and data analysis procedures. The next section presents the empirical findings, which are followed by a comprehensive discussion of those findings. In its conclusion, this paper examines the theoretical and managerial implications of the research, discusses its limitations, suggests potential avenues for future study, and provides a concluding statement.

2. Background literature

The interconnection between OGS, GAI chatbots, ELM, and SQB theory lies in their relationship to customer behavior and decision-making processes. OGS platforms utilize GAI chatbots to optimize user experience through tailored recommendations and support. The ELM is relevant because it elucidates the two pathways of persuasion: central and peripheral.

When it comes to OGS, consumers can use central processing to make selections based on product attributes and quality or peripheral processing influenced by the convenience and efficiency of AI chatbot interactions. Moreover, the theory of SQB posits that individuals tend to prefer the current state of affairs, which can deter them from embracing new shopping practices. AI chatbots in OGS can serve as persuasive instruments to counteract SQB by introducing inventive and effective shopping methods, ultimately impacting consumer decisions through a blend of central and peripheral channels of persuasion.

2.1. Online grocery shopping (OGS)

The online grocery business is projected to emerge as a significant online retail sector in the near future (Blut, Chowdhry, Mittal, & Brock, 2015; Singh, 2019). OGS falls under the retail category characterized by the acquisition of food and household essentials through online ordering processes conducted via websites or mobile applications (Beynon-Davies, 2018). The average revenue per OGS user is anticipated to reach US$449.00 by the year 2023 (Statista, 2023). Some shoppers perceive OGS to be less advantageous and more complex than in-store shopping, yet the rising preference for a hassle-free and convenient online shopping experience is driving the increasing popularity of OGS among customers. Additionally, situational factors also contribute to its adoption (Van Droogenbroeck & Van Hove, 2017).

OGS has been researched extensively in the last few years from a range of domains, such as shopper characteristics, antecedents of OGS and role of gender, factors affecting OGS adoption (Singh & Söderlund, 2020), the role of retailers and competitors in switching to OGS (Ramus & Asger Nielsen, 2005), and determinants of satisfaction with OGS (Singh & Söderlund, 2020). Past studies have categorized groups of shoppers into super-shoppers or those who resist shopping, where women are found to be keener to adopt OGS services due to their role as homemakers (Van, 2022). Website design, product quality and delivery were also found to be crucial in adopting OGS.

2.2. Generative AI chatbots

GAI chatbots are online services powered by AI algorithms that use large language models to help in real-time query resolution, content creation, marketing automation, and many other tasks (Kushwaha & Kar, 2021; Ooi et al., 2023; Kar et al., 2023). GAI chatbots like Alexa, Siri, and Google Assistant are becoming a part of consumers' households and daily lives (Singh, 2022). These GAI chatbots engage in conversations with customers, utilizing text or voice communication, to address a wide range of inquiries and fulfill diverse customer needs (Crolic, Thomaz, Hadi, & Stephen, 2022). Their responses are sometimes generated based on interaction and knowledge documented on the internet while using GAI and large language models (Kar et al., 2023). Recognizing their growing appeal, grocery retailers are formulating marketing strategies to actively engage the consumer using GAI chatbots (Bygstad, 2010), which are also being leveraged to facilitate consumers' grocery purchases and encourage repeat transactions (Singh, 2022).

GAI chatbots are emerging as conduits through which consumers can access product information, make initial purchases, and facilitate repeat purchases of products and groceries (Simms, 2019). However, stakeholders tend to have different reasons for using the same GAI chatbots (Kar & Kushwaha, 2021). Offering personalized suggestions, recommendations, and support with daily chores may help increase consumers' trust in these anthropomorphized GAI chatbots and build "affectionate ties" similar to those that develop between people and other objects (Dawar & Bendle, 2018; Bygstad, 2017). GAI chatbots in OGS can also be thought of as a more personal type of relationship that incorporates and displays social value (Ford, Jain, Wadhwani, & Gupta, 2023).

2.3. Elaboration likelihood model (ELM)

ELM posits that specific factors related to central cues necessitate deep cognitive processing to influence attitude change. By contrast, those associated with peripheral cues can facilitate attitude change with minimal mental exertion (Aghakhani et al., 2021). This is because the central route involves evaluating the genuine merits of arguments—thus requiring individuals to engage in critical thinking about the information—whereas the peripheral route relies on straightforward cues that demand less cognitive effort (Chakraborty, Patre, & Tiwari, 2023; Yu, Li, He, Wang, & Jiao, 2020). The ELM suggests that both central and peripheral cues within a message simultaneously influence a message recipient's judgment, rather than operating independently, to determine whether the recipient is persuaded (Aghakhani et al., 2021).

As a framework for understanding attitude change through persuasion, ELM has been thoroughly investigated across many digital platforms, such as online dating (Chakraborty et al., 2023), the use of chatbots in customer purchase journeys (Dwivedi et al., 2023), online review credibility (Jha & Shah, 2021), social roles in voice shopping (Rhee & Choi, 2020), and trust in the online context (Srivastava & Saini, 2022). This study discusses how the operative factors in ELM and SQB theory are affecting consumer trust, which has been under-explored in the context of GAI chatbot use in OGS.

2.4. Status quo bias (SQB) theory

SQB theory seeks to elucidate why individuals tend to favor preserving their existing status or circumstances (Nel & Boshoff, 2020; Gong, Zhang, Chen, Cheung, & Lee, 2020). As such, SQB theory offers a valuable collection of theoretical insights for comprehending how the use of incumbent systems can hinder the acceptance of new information systems (Kim & Kankanhalli, 2009; Hsieh, 2015). SBQ draws upon the principles of psychological theories and finds application across a range of disciplines in the context of decision-making (Balakrishnan, Dwivedi, Hughes, & Boy, 2021).

Three distinct constructs comprehensively define SQB: psychological commitment, cognitive misperception, and rational decision-making (Samuelson & Zeckhauser, 1988; Tsai, Cheng, Tsai, Hung, & Chen, 2019). Additionally, the presence of perceived uncertainty stemming from the new system can further deter users from transitioning to it (Lee & Joshi, 2017). SQB theory has been used extensively in various contexts, including health clouds (Hsieh, 2015), online health service intention (Zhang, Guo, Wu, Lai, & Vogel, 2017), mobile website purchasing resistance (Nel & Boshoff, 2020), tech renewal and user resistance (Shirish & Batuekueno, 2021), and AI-powered chatbots; this range of applications justifies its use in the present context (Balkrishnan

Table 1
Description of constructs ().

Constructs	Descriptions	Sources
Perceived Interaction Quality	Perceived Interaction Quality refers to the subjective assessment of the overall efficacy and satisfaction in an encounter. It includes variables such as clarity of communication, responsiveness, and mutual comprehension.	(Pelau et al., 2021)
Perceived Credibility	Perceived credibility pertains to an individual's personal evaluation of the dependability, knowledge, and consistency of a source or communicator within a certain situation.	(Chung & Han, 2017)
Perceived Inertia	Perceived inertia is the resistance or hesitation that individuals feel when it comes to changing their current habits, behaviors, or preferences. This resistance is influenced by factors such as comfort, familiarity, and the perceived effort needed for change.	(Hsieh & Lin, 2018)
Perceived Threat	Perceived threat is the personal evaluation of the degree of risk or harm presented by a particular stimulus, setting, or situation, which affects emotional and cognitive reactions.	(Balakrishnan et al., 2021)
Perceived Regret Avoidance	Perceived regret Avoidance is the tendency of people to take action in the hope of avoiding future regret, with choices driven by a desire to reduce the possibility of feeling remorse or disappointment.	(Tsiros & Mittal, 2000)
Perceived Attitude towards Generative AI chatbots	Perceived attitude is the personal interpretation of how others feel, evaluate, or hold ideas about a specific person, item, idea, or circumstance.	(Balakrishnan et al., 2021)
Perceived Trust towards OGS using Generative AI chatbots	Perceived trust refers to an individual's subjective perception or confidence in the reliability, honesty, and dependability of another person, organization, or institution within a certain situation.	(Chakraborty et al., 2023; Wamba et al., 2023)
Anthropomorphism	Anthropomorphism refers to the act of ascribing human-like attributes, emotions, or characteristics to creatures, animals, or objects that are not human.	(Munnukka et al., 2022)

Source: Authors' own creation

et al., 2021). Details related to constructs, descriptions and sources of the constructs are provided in Table 1.

3. Research design

This study utilized a mixed-methods approach (i.e., incorporating both qualitative and quantitative methodologies) to mitigate the methodological constraints associated with studies that rely exclusively on a single method (Turner, Cardinal, & Burton, 2017). The utilization of mixed-methods research is essential because it amalgamates the advantages of qualitative and quantitative research methodologies, so yielding a more all-encompassing comprehension of intricate occurrences (Patre, Chakraborty, Kar, Singu, & Tiwari, 2023). Researchers can validate results from multiple viewpoints by combining qualitative data, which provides detailed insights into individuals' experiences and views, with quantitative data, which enables statistical analysis and generalization (Venkatesh, Brown, & Bala, 2013). This methodology improves the strength and accuracy of research results, providing a more detailed and comprehensive understanding of the research topic.

Mixed methods are highly advantageous in multidisciplinary studies because they allow researchers to capture the intricate nuances of human experiences while simultaneously establishing patterns and associations that can be subjected to quantitative analysis (Patre et al., 2023). In the qualitative phase of the exploratory investigation, data analysis was conducted using semi-structured interview techniques (Jarratt, 1996); specifically, theme analysis was conducted after collecting interviewee responses (Schneider, Wheeler, & Cox, 1992). The purpose of this analysis was to identify and analyze salient constructs.

The above-mentioned parameters were employed for the purpose of identifying theoretical lexicons, which were subsequently subjected to validation in the confirmatory study. The framework under investigation in this study was developed based on theoretical lexicons, which were subsequently employed to conduct a cross-sectional confirmatory analysis in order to establish its validity. The confirmatory investigation was conducted utilizing a cross-sectional design, employing a structured questionnaire (Polisetty, Chakraborty, Kar, & Pahari, 2023).

The data analysis was conducted using structural equation modelling (SEM). After completing the analysis with the SEM-based technique, we also checked the same with the fuzzy set qualitative comparative analysis (fsQCA) technique. Although SEM has demonstrated its effectiveness in elucidating associative links, it is important to acknowledge that the ability to explain the variability of the dependent variable is constrained by the underlying assumptions of linearity inherent in regression-based models. Thus, to account for the non-linear associations and to ascertain the predictive capacities of our theoretical framework, the SEM ANN technique was employed for data analysis during the last phase of the investigation (Ashaari, Singh, Abbasi, Amran, & Liebana-Cabanillas, 2021).

4. Exploratory study (Study 1)

4.1. Sampling frame and sample size

To identify the constructs that would be examined, a series of in-depth interviews were conducted with users. This study has contributed to the advancement of our comprehension of the enablers and obstacles associated with the adoption of GAI and the subsequent effects on attitude and trust.

4.2. Method

We conducted in-depth interviews with 22 managers actively involved in AI adoption. The interviews were conducted online and lasted an average of 25 min (minimum = 18 min, maximum = 43 min). This approach enabled the interviewees to explain the reasons for the findings of the quantitative study. All of these managers had a minimum work experience of eight years and held a post-graduate degree.

4.3. Sampling procedure

The researchers conducted interviews with individuals who utilize GAI during the process of OGS and in related domains. All participants utilizing the Online Gaming Survey were requested to indicate their willingness to participate in a semi-structured interview. A total of 26 users of the Online Gaming Society consented to participate in the interviews conducted for the qualitative study.

4.4. In-depth interview administration

The interviews were carried out in three distinct phases. Consistent with the intervention methodology, the interviews commenced by posing broad inquiries and subsequently progressed toward more focused inquiries, with each query highlighting the outcomes of the quantitative investigation. The comprehensive set of questions utilized as a reference guide throughout the interviews may be found in Appendix A. Theoretical saturation was achieved after interviewing 22 of these users.

4.5. Analysis procedure

We conducted a thematic analysis of the qualitative data, using a common approach that involves the simultaneous description, analysis, and reporting of the themes and patterns identified in the collected data. Thematic analysis provides researchers with a high degree of flexibility in their evaluation and subsequent analysis of collected material. Although the authors formulated a foundational set of inquiries, the process of generating further follow-up inquiries exhibited a certain degree of adaptability because they emerged organically throughout the course of the ongoing dialogues.

Following the completion of the interviews, the audio recordings were faithfully transcribed, after which both deductive and inductive coding methodologies were employed to ascertain the codes and themes. The topic was examined through the lens of a fundamental theory, and then specific findings were documented by the authors through the use of the interview procedure. The themes were subjected to a thorough reassessment by the authors in order to determine their coherence with specific data extracts and the overall dataset. Subsequently, the themes were determined and delineated. Inter-coder reliability was established for the identified themes based on the independent assessment of three researchers. Face validity of the study's findings was evaluated through consultation with five industry specialists specializing in online grocery applications.

4.6. Findings from interviews

Coding of the interviews identified numerous factors, such as perceived interaction quality, perceived credibility, perceived inertia, perceived threat, perceived regret avoidance, perceived attitude toward GAI chatbots, perceived anthropomorphism, and perceived trust toward online shopping using GAI chatbots. The details of results obtained from the interviews (which encompass several constructions, interview excerpts, and an analysis of the responses) are illustrated in Appendix B. Based on the findings of this exploratory study, we moved toward establishing the relationship among these variables in the confirmatory study.

5. Confirmatory study (study 2)

5.1. Development of hypotheses

In this section, we explain how we build the UFTTP through the integration of ELM and SQB theory in the utilization of GAI chatbots within the context of OGS posits that chatbots possess the potential to enhance the overall customer experience through several means. For instance, chatbots possess the capability to offer clients tailored recommendations, address inquiries regarding products and services, and facilitate the completion of their purchases. In order to establish a comprehensive framework for the integration of GAI chatbots in the context of OGS, the researchers have introduced a comprehensive model.

5.1.1. Perceived interaction quality and perceived credibility

The relationship between perceived interaction quality and perceived credibility significantly influences the perceived attitude in different contexts (Aghakhani et al., 2021; Lee, Hsu, & Silva, 2020). Within the continuously growing domain of electronic commerce, GAI chatbots have emerged as indispensable partners for consumers as they navigate the complexities (Dwivedi et al., 2023; Prasad Agrawal, 2023) of OGS. The quality of interaction between users and GAI chatbots influences the perception of the process and the GAI chatbot's credibility (Aghakhani et al., 2021). As users consider the interaction quality to be characterized by seamlessness, efficiency, and user-friendliness, and the GAI chatbots to be reliable, accurate, and trustworthy, their overall attitude toward the practice of OGS experiences a notable increase in positivity (Dwivedi et al., 2023).

The interplay between the quality of interaction and the perceived credibility (Pillai, Kim, Haldorai, & Kim, 2022) of AI chatbots cultivates a feeling of trust and contentment among users, thereby developing a sense of confidence in the GAI chatbots competence to aid in product selection, provide recommendations, and facilitate secure transactions (Dwivedi et al., 2023). Consequently, people would probably exhibit a greater propensity to adopt OGS using GAI chatbots, perceiving it as a reliable and convenient medium. To achieve success in the highly competitive environment, businesses should prioritize the optimization of both perceived interaction quality and perceived credibility (Srivastava & Saini, 2022). By doing so, they can effectively positively mold customers' opinions and cultivate long-term loyalty within this dynamic retail environment (Shahab, Ghazali, & Mohtar, 2021). Hence, we hypothesize:

H1, H2: Perceived interaction quality and perceived credibility significantly impact perceived attitude toward OGS using generative AI chatbots.

5.1.2. Perceived inertia, perceived threat, and perceived regret avoidance

Within the dynamic and ever-changing realm of electronic commerce, it is crucial to acknowledge the substantial role that psychological variables play in impeding consumer acceptance and utilization (Nel & Boshoff, 2020). The concept of perceived inertia, denoting the inclination to resist change in conventional shopping practices, may result in individuals harboring skepticism and hesitation toward engaging in OGS (Hsieh, 2015). Moreover, the uncertainty and lack of trust in the online purchasing process (Balakrishnan et al., 2021), including GAI chatbots, can be attributed to the perception of potential hazards, including privacy issues and data breaches. Additionally, the apprehension of making an erroneous selection (i.e., resulting in perceived regret) may discourage consumers (Samuelson & Zeckhauser, 1988) from utilizing GAI chatbots for the purpose of OGS.

The convergence of these adverse factors might significantly affect the general perception of the convenience and effectiveness (Lee & Joshi, 2017) of OGS with GAI chatbots, hence impeding their extensive acceptance. In order to foster the adoption of this novel approach to shopping, it is imperative for businesses and service providers to actively acknowledge and mitigate these apprehensions (Shirish & Batuekueno, 2021). They should prioritize highlighting the robustness, convenience, and dependability of their AI chatbot-powered platforms as a means to counteract the negative consequences associated with perceived inertia, perceived threat, and perceived regret avoidance. Hence, we propose:

H3: Perceived inertia negatively impacts perceived attitude toward online grocery shopping using generative AI chatbots.

H4: Perceived threat negatively impacts perceived attitude toward online grocery shopping using generative AI chatbots.

H5: Perceived regret avoidance negatively impact perceived attitude toward online grocery shopping using generative AI chatbots.

5.1.3. Perceived attitude

The attitudes and views of consumers have a significant impact on developing their trust in the use of GAI chatbots as a shopping channel for groceries (Munnukka, Talvitie-Lamberg, & Maity, 2022). Users who exhibit a favorable disposition toward engaging in OGS with GAI chatbots demonstrate an increased propensity to place trust in both the system and the GAI chatbots entity (Chakraborty et al., 2023). A positive disposition is frequently established through favorable previous encounters, user-friendly functionality, perceived convenience, and contentment with the functioning of GAI chatbots (Balakrishnan et al., 2021).

The above-mentioned variables all contribute to establishing a perception of reliability and credibility in the technology (Balakrishnan et al., 2021), the merchant, and the GAI chatbot's skills. As a consequence, trust cultivates ongoing utilization and allegiance, as consumers possess a sense of assurance that the GAI chatbots will proficiently aid them, securely manage their info, and deliver a dependable buying encounter. Within the context of this symbiotic association between attitude and trust, organizations can augment consumer confidence in OGS through the utilization of GAI chatbots. This may be achieved by continually providing favorable interactions, seamless transactions, and an overall experience of superior quality (Chakraborty et al., 2023). Hence, we propose the following:

H6: Perceived attitude toward online grocery shopping (OGS) using generative AI (GAI) chatbots significantly impacts perceived trust toward OGS using GAI chatbots.

5.1.4. Perceived anthropomorphism as a moderator

Anthropomorphism, which describes the extent to which individuals see the GAI chatbots as possessing human-like attributes or features (Dwivedi et al., 2023), can substantially impact their interpretation and response to different parts of their engagement with the system (Klein & Martinez, 2022). The level of anthropomorphism exhibited by these AI chatbots influences the intricate relationships between different important elements, such as interaction quality (Dwivedi et al., 2023). The users' judgments of the AI chatbots' interaction capabilities are influenced by the extent to which they attribute human-like features to these digital entities (Dinh & Park, 2023). Furthermore, the influence of perceived anthropomorphism moderates the perceived credibility, which is another important element.

AI chatbots' credibility and reliability are closely linked to consumers' impressions of their human-like characteristics (Klein & Martinez, 2022). As consumers perceive chatbots to contain human-like features, their evaluations of the chatbots' believability are likely to improve accordingly (Munnkka et al., 2022). Within the framework of perceived interaction quality and perceived credibility, those who regard the GAI chatbots as possessing greater human-like qualities may exhibit a greater propensity to overlook minor interaction faults or restrictions (Dinh & Park, 2023); these users attribute such imperfections to the intrinsic intricacy of human-like interactions (Klein & Martinez, 2022). The enhancement of interaction quality and credibility can strengthen the favorable influence on the general attitude (Munnkka et al., 2022) toward OGS using GAI chatbots. The users' inclination toward inertia (i.e., their reluctance to change or adapt) is influenced by the degree to which they attribute human characteristics to the AI chatbots (Chi, Denton, & Gursoy, 2020). While dealing with OGS through GAI chatbots, users' perceptions of threat and their desire to prevent regret (Balakrishnan, Abed, & Jones, 2022) are influenced by the human-like qualities that users attribute to these digital entities.

Furthermore, perceived anthropomorphism may amplify the perception of inertia, as users may exhibit greater resistance to change when they anthropomorphize the intelligent virtual helper, perceiving it as similar to a familiar human helper (Dinh & Park, 2023). Likewise, the process of humanizing the GAI chatbots has the potential to heighten the perception of threat among users. This is due to users' increased apprehension regarding potential privacy infringements or unethical conduct, as people tend to attribute human intentions to the technology (Klein & Martinez, 2022). Moreover, the amplification of the impact of perceived regret avoidance by perceived anthropomorphism can be observed, as individuals may feel a heightened sense of regret when they perceive the GAI chatbots as a quasi-human being with whom they could have had a more profound bond (Balakrishnan et al., 2022).

The comprehension and effective handling of perceived anthropomorphism holds significant importance for businesses and developers, as it has the potential to either augment or complicate the interaction between these elements, ultimately influencing consumers' perceptions and behaviors (Klein & Martinez, 2022) in relation to OGS with GAI chatbots. By strategically and effectively controlling the anthropomorphic attributes of GAI chatbots, organizations may enhance the user experience and exert a favorable impact on attitudes, trust, and adoption rates within the dynamic retail environment (Dinh & Park, 2023). Hence, we propose:

H7a-7e: Perceived anthropomorphism has a moderating influence on the associations between perceived interaction quality, perceived credibility, perceived inertia, perceived threat, perceived regret avoidance and perceived attitude toward OGS using generative AI chatbots.

H7f: Perceived anthropomorphism moderates the associations between perceived attitude and perceived trust toward online grocery shopping using generative AI chatbots. Fig. 1 describes the hypothesized model.

5.2. Research methodology

5.2.1. Data collection

An online survey was conducted using a structured questionnaire to gather data from individuals who used GAI chatbots for OGS. The research employed a descriptive research design and purposive sampling technique to gather the participants' replies. The questionnaire was adapted and customized to align with the specific context of the OGS, drawing from established scales found in the existing literature. The primary objective of this study is to assess the underlying factors influencing the attitude and trust toward OGS using GAI chatbots. This investigation will focus on the use of well-established OGS platforms, including Big Basket, Grofers, Amazon Pantry, and Reliance Jiomart, which are widely used among consumers of grocery items. We identified possible users of these services based on comments and likes of these platforms on Facebook.

The data collection process employed a purposive sampling strategy to ascertain participants' eligibility, and a series of questions were posed to potential replies. The questionnaire was initially distributed to a sample of 39 users and management professors in order to assess the validity and appropriateness of the questions. This process facilitated the revision of some questions in order to address concerns related to language and ambiguity. Following revisions, the questionnaire was distributed to the prospective participants via email, WhatsApp, LinkedIn, and Facebook. The survey instrument was developed using Google Forms, restricting replies to those meeting the predetermined inclusion criteria. Data was collected from April 2022 to December 2022. The screening questions were first used to identify those who were users of OGS and had used GAI chatbots at the time of using OGS. The screening questions were:

(1) Are you a user of any online grocery shopping (OGS) platforms (Big Basket, Grofers, Amazon Pantry, and Reliance Jiomart)?
(2) Have you used generative AI chatbots at the time of using OGS?

If they answered "yes" to both the answers, respondents could see the next questions. Among the sample of more than 3,000 users who were reached, 372 consented to participate by completing the required forms and submitting their responses. A total of 372 responses were obtained, as the Google Form utilized did not allow for the submission of incomplete responses. The participants in this study exhibit diversity in terms of gender, income level, and household size. Table 2 provides a comprehensive depiction of the demographic analysis. The demographic details show that 71 % of the population is female, 45 % of respondents earn less than or equal to 500, and 66 % are graduates and private

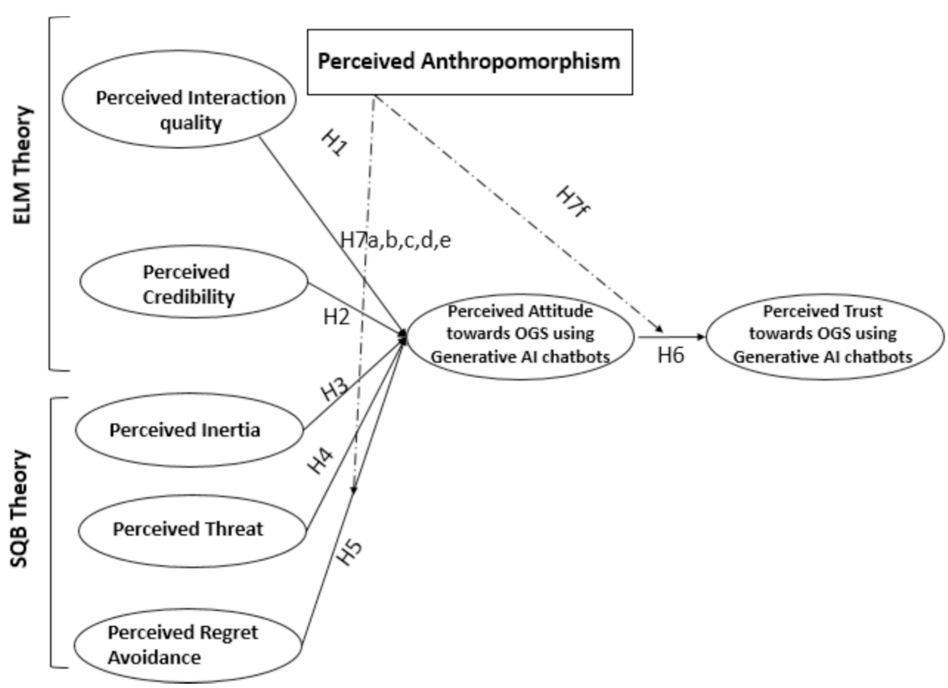

Fig. 1. Hypothesized model ().
Source: Authors' own creation

Table 2
Demographic details ().

Demographic Measures	Items	Count	Percent
Gender	Male	108	29 %
	Female	264	71 %
Income	Less than and equal to 500 USD	166	45 %
	501 – 700 USD	34	9 %
	701——900 USD	16	4 %
	901 USD and more	156	42 %
Education	Graduate	245	66 %
	Post Graduate	98	26 %
	Above Post Graduate	29	8 %
Occupation	Self Employed	85	23 %
	Private Employee	244	66 %
	Government Employee	41	11 %
	Retired	2	1 %

Source: Authors' own creation

employees (Table 2).

In order to assess the appropriateness of our sample size for model testing, we employed the Kaiser–Meyer–Olkin measure of sampling adequacy, which resulted in a value of 0.86 for the sample size. Prior research has indicated that a score ranging from 0.80 to 1.0 signifies that the sample size is sufficient for conducting model testing (Cheffi, Zahir-ul-Hassan, Farooq, Baqrain, & Mansour, 2023).

5.2.2. Data analysis

The data analysis in this study employed a three-step technique. First, confirmatory factor analysis (CFA) was conducted to assess the construct validity and internal consistency reliability of the measurement scales. This study employed the SEM technique to examine the conceptual framework, utilizing both SPSS 26 and Amos 26 software. The moderation test has been done using the PROCESS Macro 4.0 tool.

Second, fsQCA techniques have been used, which are multifunctional instruments that facilitate the examination and elucidation of complex causal connections. This is complementary to the SEM-based analysis and helps to uncover different combinations of variables, which aid in explaining different levels of trust.

Third and finally, predictive analysis has been undertaken with the help of artificial neural networks (ANNs). Whereas the SEM and fsQCA help uncover causal behavior, the ANN helps establish predictive capabilities of the theoretical model through a black box view. The details of this analysis are documented in section 5.5.

5.3. Findings

The presence of missing values in the data was initially assessed, and it was found that no missing values were present. Additionally, the normalcy of the data was evaluated, and it was found to fall within the acceptable range of 1 and 7 for both skewness and kurtosis. The values observed for the study constructs were comfortably within the range of −3 to + 3. The presence of multi-collinearity in the dataset was assessed by calculating the variance inflation factors, which were determined to be below the threshold of 3, indicating an acceptable level of multi-collinearity. Using the Harman one-factor test, the researchers conducted an exploratory factor analysis to test for common method bias (CMB). The data presented in the study indicates that there is no evidence of CMB. Specifically, it was shown that less than 50 % of the variance can be attributed to a single factor. After conducting the CMB test, CFA was employed to validate the model, as shown in Table 2. The construct-wise sources are also provided in Table 3, and the questionnaire is available in Appendix C.

Each construct's composite reliability (CR) exhibited internal consistency, with values exceeding 0.7 (Table 3). The constructs have been demonstrated to have convergent validity, as evidenced by average variance extracted (AVE) values exceeding 0.5. According to Fornell and Larcker (1981), it is evident that the underlying variables account for a minimum of 50 % of the variance observed in their corresponding indicators. The model's discriminant validity was assessed by employing various criteria, including the Fornell–Larcker criterion, the requirement for AVE to be greater than maximum shared variance (MSV), and the application of the heterotrait–monotrait (HTMT) method.

Table 3
Measurement of study variables ().

Factors	Source	Items code	CFA
Perceived Interaction Quality	(Pelau et al., 2021)	PIQ1	0.787
		PIQ2	0.745
		PIQ3	0.857
		PIQ4	0.727
Perceived Credibility	(Chung & Han, 2017)	PCI1	0.803
		PCI2	0.740
		PCI3	0.670
Perceived Inertia	(Hsieh & Lin, 2018)	PEI1	0.844
		PEI2	0.851
		PEI3	0.854
Perceived Threat	(Balakrishnan et al., 2021)	PET1	0.882
		PET2	0.875
		PET3	0.914
Perceived Regret Avoidance	(Tsiros & Mittal, 2000)	PRA1	0.794
		PRA2	0.760
		PRA3	0.732
Perceived Attitude towards GenerativeAI chatbots	(Balakrishnan et al., 2021)	PAI1	0.876
		PAI2	0.864
		PAI3	0.862
Perceived Trust towards Generative AI chatbots	(Chakraborty et al., 2023; Wamba et al., 2023)	PTT1	0.855
		PTT2	0.698
		PTT3	0.704
Perceived Anthropomorphism	(Munnukka et al., 2022)	ANT1	0.677
		ANT2	0.789
		ANT3	0.695

Source: Authors' own creation

The coefficients associated with the other constructs, as seen in Table 4, exhibit values that are lower than the squared AVE, whereas the AVE values are greater than the MSV. Therefore, the constructs provided in this study are assigned to discriminant validity, and the model will be tested afterwards. Following Henseler, Ringle, and Sarstedt (2015), while comparing the Fornell–Larcker criterion and the assessment of cross-loadings, it was shown that the HTMT technique exhibited more sensitivity in detecting the discriminant validity of conceptions (Table 5). In order to ensure sufficient discriminant validity of constructs, it is recommended that HTMT ratio of correlations remain below the threshold of 0.85.

The findings indicate that the HTMT ratios exhibit values below 0.85, establishing discriminant validity. The study model's goodness-of-fit was further evaluated using covariance structure analysis in the AMOS software. The study model's model-fit metrics (for measurement model), including CMIN/DF = 1.283, AGFI = 0.918, IFI = 0.986, TLI = 982, RMSEA = 0.028, NFI = 0.938, and CFI = 0.985, are all observed to fall within acceptable thresholds. In the case of the structural model, the model-fit matrices are CMIN/DF = 1.360, AGFI = 0.922, IFI = 0.984, TLI = 981, RMSEA = 0.031, NFI = 0.943, CFI = 0.984. The R^2 of PAI and PTT are 48.5 % & 24.7 %, respectively.

5.4. Hypothesis validation

When testing the hypothesis of direct effect, the moderation effect of anthropomorphism has been tested through PROCESS Macro. Furthermore, H1, H2, H3, H4, and H6 posited significant association with PAI and PTT. According to the results presented in Table 6, PCI are PIQ are positively and significantly related to PAI; thus, H1 and H2 are supported. On the other hand, H3 and H4 posited that PEI and PET are negatively but significantly associated with the PAI; thus, H3 and H4 are accepted. H5 stated that PRA is negatively related to PAI, but it is not significant. At the same time, we have also found that PAI has a positive

Table 4
Validity analysis ().

	CR	AVE	MSV	MaxR (H)	PEI	PIQ	PET	PRA	PCI	PAI	PTT	ANT
PEI	0.886	0.722	0.352	0.886	**0.85**							
PIQ	0.861	0.609	0.191	0.871	0.132*	**0.78**						
PET	0.92	0.793	0.352	0.922	0.594***	−0.081	**0.89**					
PRA	0.806	0.582	0.087	0.809	0.262***	−0.183**	0.200**	**0.763**				
PCI	0.783	0.547	0.28	0.793	−0.218***	0.405***	−0.301***	−0.155*	**0.739**			
PAI	0.901	0.753	0.286	0.902	−0.388***	0.437***	−0.423***	−0.295***	0.529***	**0.868**		
PTT	0.798	0.571	0.234	0.823	−0.053	0.352***	−0.076	−0.092	0.447***	0.484***	**0.756**	
ANT	0.765	0.521	0.286	0.774	0.019	0.376***	−0.116†	0.013	0.499***	0.534***	0.443***	**0.722**

Source: Authors' own creation

Table 5
HTMT analysis ().

	PEI	PIQ	PET	PRA	PCI	PAI	PTT	ANT
PEI								
PIQ	0.103							
PET	0.539	0.073						
PRA	0.222	0.152	0.175					
PCI	0.18	0.345	0.26	0.126				
PAI	0.348	0.391	0.387	0.254	0.439			
PTT	0.064	0.295	0.074	0.082	0.358	0.422		
ANT	0.029	0.304	0.092	0.013	0.385	0.442	0.334	

Source: Authors' own creation

Table 6
Standardized regression weights ().

Path			Estimate	S.E.	C.R.	P	Accept/ Reject	Hypothesis
PAI	<—	PCI	0.359	0.075	4.796	***	Accept	H2
PAI	<—	PIQ	0.376	0.067	5.612	***	Accept	H1
PAI	<—	PEI	−0.248	0.063	−3.936	***	Accept	H3
PAI	<—	PET	−0.106	0.049	−2.134	0.033	Accept	H4
PAI	<—	PRA	−0.104	0.059	−1.751	0.08	Reject	H5
PTT	<—	PAI	0.44	0.056	7.907	***	Accept	H6

Source: Authors' own creation

and significant effect on PTT; thus, H5 is rejected and H6 is accepted.

The research employed the SPSS PROCESS Macro tool, specifically model 1, to examine the moderating impact of ANT on the hypothesized association between PCI, PIQ, PEI, PET, PRA, and PAI. This analysis is presented in Table 7 and Fig. 2. The results suggest that there is no moderating influence of anthropomorphism on the relationship between PEI, PRA, and PAI, as well as with PAI and PTT. However, it is seen that anthropomorphism exhibits a moderating effect on the association between PCI, PIQ, PET, and PAI, as posited in other hypotheses.

5.5. *Fuzzy set qualitative comparative analysis (fsQCA)*

The theoretical underpinning of SEM is rooted in the concept of correlational causation. The presence of symmetry in correlations indicates the existence of causal symmetry, implying that the values of the independent variables influence the values of the dependent variable, whether they are low or high. Nevertheless, it is important to note that the validity of this assertion may be compromised by the inherent asymmetry that characterizes interactions. fsQCA tackles these concerns and enables researchers to discern asymmetrical linkages within the conceptual framework under investigation. According to Pappas, Papavlasopoulou, Mikalef, and Giannakos (2020), the fsQCA method three several stages: (1) calibration, which involves the conversion of data into fuzzy scores; (2) construction and refinement of the truth table; and (3) the analysis of viable solutions. The data obtained from a total of 372 samples were subjected to reanalysis utilizing the fsQCA software package version 3.0. In accordance with previous studies, the scale was calibrated using three distinct reference points: a score of 4 denoting full membership, a score of 3 indicating the crossover point, and a score of 2 representing full non-membership (Pappas & Woodside, 2021).

The truth table that was created underwent refinement through the application of specific criteria, namely a minimum frequency and consistency cut-off. The outcome of this phenomenon leads to several trajectories toward perceived trust, wherein the trajectory deemed

Table 7
The moderating effect of anthropomorphism (ANT) ().

Path			β	SE	t	P	LLCI	ULCI	Moderation	Hypothesis
PAI	<—	PCI	−0.11	0.04	−2.72	0.01	−0.18	0.03	Yes	H7a
PAI	<—	PIQ	−0.17	0.04	−4.21	0.00	−0.25	−0.09	Yes	H7b
PAI	<—	PEI	0.02	0.03	0.60	0.55	−0.05	0.09	No	H7c
PAI	<—	PET	0.09	0.03	2.83	0.00	0.03	0.16	Yes	H7d
PAI	<—	PRA	0.03	0.04	0.73	0.46	−0.06	0.12	No	H7e
PTT	<—	PAI	0.05	0.04	1.42	0.16	−0.02	0.13	No	H7f

Source: Authors' own creation

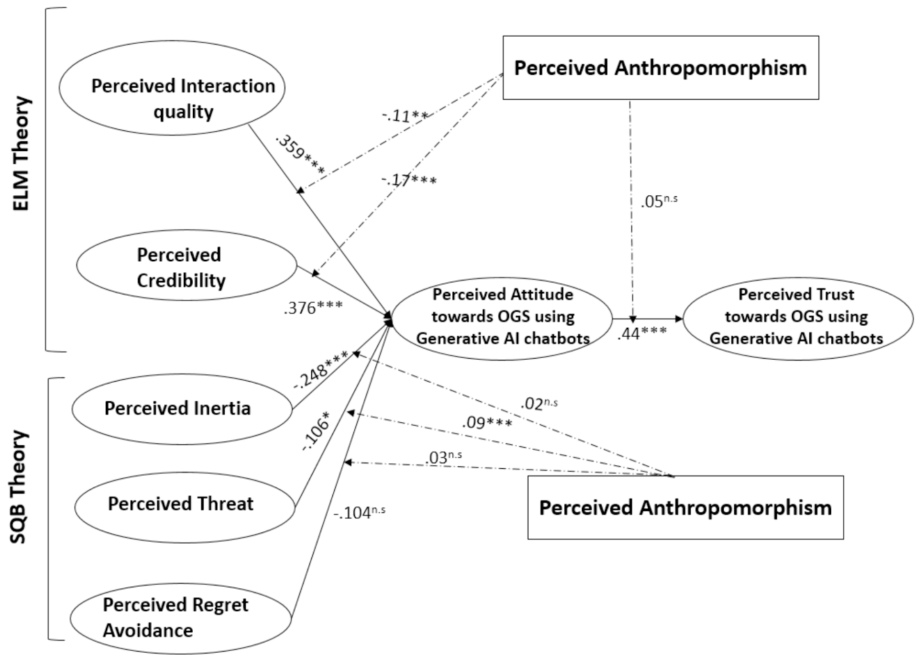

Fig. 2. Results of the model ().
Source: Authors' own creation

acceptable should exhibit a consistency level of more than 0.75. Additionally, the acceptable range for raw coverage should fall within the interval of 0.25 to 0.65, and unique coverage more than 0.1, allowing for minor fluctuations within this range to be deemed acceptable (Pappas & Woodside, 2021).

Table 8 displays the fsQCA findings, which demonstrate the existence of 14 distinct pathways that contribute to the development of trust. The initial pathway (pathway 1) posits that the absence of core conditions on perceived threat and perceived regret avoidance are associated with high trust. Conversely, the subsequent pathway (pathway 2) indicates that increased perceived credibility (presence of core condition) and absence of perceived threat (absence of peripheral condition) are linked to high levels of trust, and so on. For example, FPCI (calibrated factor) is present in both the parsimonious and intermediate solutions; it has high raw coverage, unique coverage and consistency, and it is considered a core condition because it is available on both solutions and has high explanatory power.

All the pathways encompassed the elements of PCI, PIQ, PEI, PET, PRA, and PAI, thus implying that these factors are important for the attainment of trust. The SEM analysis findings revealed that all the variables have statistically significant effects on trust except PRA. However, the association between PCI, PIQ, PEI, and PAI on PTT was further supported by the fsQCA results in all paths, which were deemed viable alternatives because their coverage fell within the range of 0.25 to 0.65 and their consistency exceeded the threshold of 0.75. The high overall solution coverage and consistency (more than 0.8) suggest that the generated configurations have significant empirical relevance.

The analysis of necessary conditions has been illustrated in Table 9. It illustrates how FPCI has the highest consistency and coverage; hence, it is the strongest variable, which explains the variations in the outcome variable trust. In this context, FPAI is the second most influential variable, which has a reasonably strong relationship with the outcome variable. However, the other variables (i.e., FPIQ, FPEI, FPRA and FPET) all have low consistency and moderate/high coverage, which may indicate weaker relationships with trust.

5.6. *Predictive analysis*

ANN was employed for predictive analysis on the comparative significance of stimulus components in pro-environmental consumption behavior. This study utilized the parameters derived from SEM path analysis as input neurons for the ANN model. The study employed multilayer perceptron and feed-forward backward-propagation neural networks. The activation of the hidden and output layers was achieved through the utilization of sigmoid functions. We utilized a 10-fold ANN analysis, wherein our model was assessed by testing it on only 30 % of the data and training it on the remaining 70 %. The SPSS findings yielded the predictor parameters that were deemed relevant for the neurons in the ANN model. A 10-fold cross-validation methodology was employed to obtain the root mean square of errors (RMSE) to mitigate the over-fitting risk. As evidenced by the data presented in Table 10, the mean values of the training and testing RMSE are low. Consequently, we assert that the model exhibits a strong fit with the data.

The authors conducted a sensitivity analysis (Table 11) to determine each input neuron's normalized significance. This was achieved by dividing the relative importance of each neuron by the maximum importance value, and expressing the result as a percentage. The findings indicate that the PAI variable emerges as the primary predictor, exhibiting an average importance of 28 %. Following closely, the PCI variable assumes the second most influential predictor role, displaying a normalized importance of 93 %. The subsequent category is PIQ, with a normalized importance of 68 %, succeeded by PEI at 41 %, PET at 28 %, and PRA at 21 %.

6. Discussion

The proposed UFTTP has been introduced from this study as a comprehensive model that illustrates the effect of factors from ELM and SQB theory toward trust. Perceived interaction quality (PIQ) is crucial in influencing consumers' attitudes toward OGS when they utilize GAI chatbots (H1). In this rapidly evolving digital environment, where technology plays an increasingly prominent role in our daily activities, the level of engagement with GAI chatbots becomes a crucial determinant of users' overall perceptions and attitudes. The evaluation of PIQ is

Table 8
Results of fsQCA ().

Pathway	FPCI	FPIQ	FPEI	FPET	FPRA	FPAI	Raw coverage	Unique coverage	Consistency
~FPET*~FPRA				⊗	⊗		0.251064	0.00149488	0.817728
FPCI*~FPET	⬤			⊗			0.474146	0.011614	0.828366
FPCI*FPEI	⬤		⬤				0.505807	0.0184368	0.83944
FPCI*FPIQ*FPAI	●	●				●	0.517383	0.139101	0.872866
FPCI*FPRA*FPAI	●				●	●	0.507954	0.0527806	0.869326
~FPIQ*~FPEI*~FPET*FPAI		ⓧ	ⓧ	ⓧ		●	0.206869	0.0483344	0.822588
FPIQ*~FPET*FPRA*FPAI		●		ⓧ	●	●	0.226877	0.0124574	0.873138
FPCI*FPIQ*FPEI*FPRA	●	●	●		●		0.312546	0.00682276	0.874986
FPCI*FPIQ*FPET*FPRA	●	●		●	●		0.245774	0.00241482	0.891546
FPEI*FPET*FPRA*FPAI			●	●	●	●	0.272107	0.017862	0.881206
~FPCI*~FPIQ*~FPET*~FPRA*~FPAI	ⓧ	ⓧ		ⓧ	ⓧ	ⓧ	0.030511	0.00149494	0.758095
~FPCI*FPIQ*FPEI*~FPRA*~FPAI	ⓧ	●	●		ⓧ	ⓧ	0.041052	0.00705278	0.9614
FPCI*~FPIQ*~FPEI*~FPET*FPRA	●	ⓧ	ⓧ	ⓧ	●		0.151903	0.0093143	0.876189
FPCI*~FPIQ*FPEI*FPET*~FPAI	●	ⓧ	●	●		ⓧ	0.075051	0.0175169	0.811775
Solution coverage: 0.822991									
Solution consistency: 0.814993									

Notes: ⬤ stands for the presence of core condition; ⊗ stands for absence of core condition; ● stands for the presence of peripheral condition; ⓧ stands for the presence of absence of peripheral condition; Blank space stands for don't care(causal condition may either be present or absent).
Source: Authors' own creation

Table 9
Analysis of necessary conditions ().

Conditions Tested	Consistency	Coverage
FPAI	0.843152	0.804219
FPCI	0.856377	0.794495
FPIQ	0.621258	0.833359
FPEI	0.571543	0.751904
FPRA	0.677757	0.723664
FPET	0.528499	0.727676

Notes: Outcome variable: FPTT.
Source: Authors' own creation

comprehensive, taking into account several elements, including the AI chatbot's responsiveness, accuracy, and user-friendliness. When people perceive these encounters as speedy, helpful and seamless, their attitudes toward OGS facilitated by AI chatbots tend to be more positive. On the other hand, a below-average engagement experience can result in skepticism or hesitancy. The correlation between PIQ and attitude underscores the importance of enhancing user experiences in e-commerce, urging greater use of AI chatbot technology to enhance OGS. Perceived credibility significantly influences attitudes toward OGS with GAI chatbots. Thus, it is critical to ensure the legitimacy of AI-driven systems is crucial as consumers increasingly rely on them in the evolving e-commerce landscape.

Table 10
RMSE values ().

Network	Sum of square error (Training)	Sum of square error (Testing)	RMSE (Training)	RMSE (Testing)	Sample size (Training)	Sample size (Testing)	Total sample size
1	93.982	40.402	0.592	0.623	268	104	372
2	99.63	42.337	0.626	0.599	254	118	372
3	94.66	37.596	0.612	0.562	253	119	372
4	92.547	39.959	0.604	0.582	254	118	372
5	98.726	32.04	0.605	0.56	270	102	372
6	99.184	42.952	0.626	0.601	253	119	372
7	97.886	40.924	0.612	0.607	261	111	372
8	95.034	27.918	0.603	0.502	261	111	372
9	100.772	32.047	0.612	0.558	269	103	372
10	92.549	57.345	0.597	0.716	260	112	372
Mean	96.497	39.352	0.609	0.591			
SD	2.91956	7.6825	0.01065	0.05286			

Source: Authors' own creation

Users assess credibility across dimensions such as AI chatbot precision, security efficacy, and order processing reliability. Higher perceived credibility leads to more positive attitudes toward OGS with GAI chatbots, fostering consumer confidence and convenience (Van Droogenbroeck & Van Hove, 2017). By contrast, any reservations or apprehensions regarding the trustworthiness of this way of shopping can undermine users' trust and belief in it. Therefore, it is crucial to enhance GAI chatbots' perceived credibility to cultivate positive attitudes, which will promote the widespread acceptance and effectiveness of OGS facilitated by these digital companions (Beynon-Davies, 2018).

The integration of GAI chatbots with OGS has been found to result in the emergence of perceived inertia as a significant factor influencing users' sentiments. When users experience a significant degree of inertia, characterized by challenges in navigating the AI chatbot interface or adjusting to this innovative purchasing method, their sentiments tend to be less favorable (Beynon-Davies, 2018; Kumar, Salo, & Li, 2019). Conversely, when the system is viewed as being user-friendly and adaptive, it has the potential to reduce inertia and foster more favorable views. Hence, minimizing perceived inertia is crucial to encourage the adoption and acceptance of OGS with GAI chatbots. This technological advancement has the capacity to improve convenience and efficiency for consumers.

The psychological elements of perceived threat and perceived regret avoidance significantly shape users' views toward OGS when utilizing GAI chatbots. When people perceive a high level of threat in these areas, their opinions about this shopping method may be unfavorable, marked by feelings of unease and caution. In contrast, perceived regret avoidance pertains to users' inclination to evade future regret or discontentment. If individuals expect that using GAI chatbots for grocery shopping could lead to unfavorable outcomes, such as incorrect orders or overspending, they may be hesitant to adopt the technology. In that case, it is likely that their views will be less positive. To encourage the use of GAI chatbots for OGS, it is essential to reduce perceived threats and the fear of regret, thereby fostering positive attitudes.

Building user trust and confidence in GAI chatbots for OGS entails robust security measures, transparent features, and seamless, accurate transactions. Trust and attitudes toward OGS with GAI chatbots are intertwined, influencing the effectiveness of this new shopping method in a mutually reinforcing way. Individuals' level of trust in technology-driven services such as GAI chatbots for their grocery needs is substantially influenced by their perceptions about utilizing these services. Businesses and developers operating in OGS with GAI chatbots should acknowledge the significant importance of generating favorable sentiments to promote trust among users. By continually providing a fluid and user-friendly experience that matches customers' expectations, trust may be enhanced, thus promoting the broader acceptance and adoption of this disruptive purchasing method in the dynamic digital environment.

Anthropomorphism pertains to the degree to which individuals assign human-like characteristics to virtual helpers. When individuals perceive GAI chatbots to possess more human-like qualities, they are inclined to develop stronger emotional attachments to them. The presence of an emotional connection has the potential to either enhance or diminish the influence of the aforementioned aspects on individuals' perspectives. Within the framework of perceived interaction quality, individuals who engage in anthropomorphism toward GAI chatbots may exhibit a greater susceptibility to the impact of their interactions. This susceptibility arises from their heightened expectations for interactions that mirror human-like responsiveness and helpfulness. In relation to the concept of perceived credibility, the utilization of anthropomorphism has the potential to elicit a heightened level of critical evaluation from users. One could anticipate that GAI chatbots would possess a level of trustworthiness comparable to that of human encounters. If the GAI chatbot's credibility is lacking, individuals who engage in anthropomorphism may experience heightened disappointment, which could result in a more unfavorable disposition. Individuals who engage in anthropomorphism toward GAI chatbots may have an increased sense of threat when they perceive their relationship with the AI chatbot to possess more human-like qualities. This phenomenon can engender heightened apprehensions regarding privacy and security, potentially exerting a detrimental impact on individuals' attitudes.

When users ascribe anthropomorphic characteristics to the chatbots, there is a possibility that these perceptions can enhance the overall quality and credibility of the encounter, mitigate perceived dangers, and therefore cultivate a more favorable attitude toward OGS. The user's perception of chatbots, as if they were human, can significantly influence their whole experience, affecting their trust, contentment, and readiness to accept AI-driven solutions in the context of online purchasing. Comprehending and utilizing this interaction is essential for firms and developers seeking to enhance user experiences and attitudes in the changing field of AI-supported online retail. Users should adopt a pragmatic perspective when engaging with these AI-driven interfaces, recognizing their non-human nature and prioritizing the practical features of the technology rather than ascribing human-like characteristics. In these cases, the degree of anthropomorphism is unlikely to have a substantial effect on the perceived level of effort or resistance to change (perceived inertia) and the expectation of future regret (perceived regret avoidance). It is important for developers and organizations to understand that the influence of perceived anthropomorphism on user attitudes may vary depending on the specific domain and context of the encounter. Recognizing these variances is essential for tailoring strategies accordingly.

Despite the anticipated role of perceived anthropomorphism in moderating the association between perceived attitude and perceived trust in the case of OGS using GAI chatbots, there may be situations where this influence is restricted or absent. Users can interact with AI chatbots while acknowledging their non-human essence, perceiving them as tools rather than creatures possessing human-like attributes. In

Table 11
Sensitivity analysis ().

	Importance_1	Importance_2	Importance_3	Importance_4	Importance_5	Importance_6	Importance_7	Importance_8	Importance_9	Importance_10	Average Importance	Normalized Importance (%)	Rank
PAI	0.275	0.344	0.258	0.283	0.297	0.439	0.266	0.245	0.219	0.223	0.28	100 %	1st
PCI	0.222	0.242	0.239	0.247	0.235	0.216	0.358	0.283	0.280	0.325	0.26	93 %	2nd
PIQ	0.141	0.132	0.303	0.180	0.225	0.144	0.199	0.248	0.138	0.225	0.19	68 %	3rd
PEI	0.222	0.080	0.065	0.166	0.112	0.042	0.091	0.117	0.202	0.079	0.12	41 %	4th
PET	0.092	0.127	0.037	0.059	0.060	0.111	0.047	0.090	0.123	0.054	0.08	28 %	5th
PRA	0.049	0.076	0.098	0.065	0.071	0.047	0.037	0.017	0.037	0.094	0.06	21 %	6th

Source: Authors' own creation

these instances, the degree of anthropomorphism may not have a substantial impact on the correlation between users' attitudes toward OGS and their faith in the system. Users can develop attitudes toward AI chatbots based on aspects including system functionality, efficiency, and overall user experience. Furthermore, users' confidence in AI-powered systems can be impacted by various other aspects, including the dependability, safety, and openness of the system. If these elements are given greater importance in influencing trust, the influence of perceived anthropomorphism on the relationship between attitudes and trust may be diminished. It is important to recognize that the influence of perceived anthropomorphism on the relationship between perceived attitude and perceived trust may not be consistent and can differ depending on the user's context and preferences.

Here, we argue that different combinations (or configurations) of enablers and barriers can explain users' trust toward GAI chatbots in the context of OGS. To identify such combinations, we build on complexity and configuration theories and propose a conceptual model that includes enablers and barriers. The results identify multiple combinations that explain high trust in GAI chatbots. In detail, the findings show that perceived credibility is present (i.e., high) in eight out of 10 solutions and in two combinations as a core factor, suggesting that perceived credibility plays a critical role in driving user trust. Consumers exhibit a higher propensity to place trust in a chatbot when they consider it to possess qualities of credibility and knowledge. This phenomenon may be attributable to the consumer's desire for a sense of assurance over the GAI chatbot's capacity to furnish them with precise information and well-founded recommendations. The perception of a GAI chatbot as a dependable source of information is heightened when it is deemed credible. This phenomenon can be attributed to consumers' tendency to place greater trust in a GAI chatbot that is perceived as reliable, leading them to perceive the information provided by the chatbot as neutral and truthful. A GAI chatbot that possesses credibility is more likely to be perceived as a reliable and dependable counsel.

Our findings show that perceived threats are present (i.e., high) in seven out of nine solutions. There are apprehensions over the safeguarding of individuals' personal data. Multiple concerns around the potential compromise or theft of personal data are prevalent among consumers. There are apprehensions over the utilization of personal data for advertising or commercial objectives. There is also a growing apprehension among consumers regarding the potential utilization of their personal data for the purpose of targeting them with unsolicited advertising or marketing communications. There are apprehensions over the potential misapplication of personal data by artificial intelligence chatbots. The potential utilization of AI chatbots for manipulation or deception is another matter of concern among consumers.

The utilization of GAI chatbots encompasses both enablers and barriers. Therefore, in order to enhance our comprehension of their usage, it is imperative to examine internal aspects that may contribute to the development of greater user trust. Similar to other online services, the utilization of GAI chatbots may yield various facilitating elements. Given that individuals encounter diverse obstacles while using GAI chatbots, our research outcomes offer distinct solutions that elucidate the aspects enabling and hindering different user groups. Specific patterns of users who consider these characteristics to be important and are significantly influenced by them in terms of trust are identified.

6.1. Theoretical implications

Enhancing users' OGS experiences and facilitating their trust through GAI chatbots is a crucial dimension of forthcoming human–computer interaction. Hence, this work has few theoretical implications.

First, the present study introduces a novel conceptual framework, UFTTP, which aims to elucidate the influence of various factors, both facilitating and inhibiting, on individuals' attitudes and trust with regard to OGS. This model represents a novel and contemporary approach in the realm of digital service adoption, which has been substantiated through confirmatory methodology.

Second, this study contributes to the existing literature on attitude and trust by exploring the role of barriers, specifically PEI, PET and PRA, in shaping perceived trust using UFTTP. Furthermore, this study investigates how positive and negative determinants interact to enhance or diminish the impact of these barriers.

Third, this study makes a scholarly contribution by examining the moderating influence of perceived anthropomorphism on all the associations among enablers, barriers, attitude and trust. This investigation establishes novel connections among these factors that prior research has not explored extensively.

Fourth, the incorporation of GAI poses a significant threat to conventional customer engagement strategies. This phenomenon raises questions regarding the progression of human–computer contact and how individuals acclimate to this technological advancement. It is essential to use the proposed theoretical frameworks to effectively incorporate the ever-changing dynamics of AI chatbot interactions and their impact on users' decision-making processes.

Fifth, according to ELM, people process information in two ways: the central route (which involves careful analysis and persuasive arguments) and the peripheral route (which relies on heuristics and signals without much thought). Building trust in AI-supported online shopping may require the provision of clear and convincing information about GAI chatbots' capabilities and reliability through central route processing. Trust can also be built by intuitive interfaces, endorsements, and visible brand associations. We can tailor tactics to users' information processing preferences by acknowledging and accommodating the two processing channels in the ELM. This may affect users' trust in AI-driven online grocery purchasing.

Sixth, SQB theory states that humans prefer the status quo and oppose change. Therefore, it is crucial to recognize and overcome resistance while switching from traditional to AI-powered OGS with GAI chatbots. Developers and businesses may develop interfaces that eliminate perceived disruptions, prioritize user-friendliness, and demonstrate how AI chatbots improve the buying experience. One can overcome reluctance to shift by using the SQB and offering incentives or prizes to adopt the new AI-assisted technique. Integrating ELM and SQB theory can improve trust and user acceptance in GAI chatbot-enabled OGS. This method considers cognitive processing pathways and the natural tendency to maintain the status quo.

Finally, the advent of GAI chatbots gives rise to questions about their implications for conventional grocery shopping, encompassing the philosophy of customer decision-making and the notion of convenience. In order to comprehend the impact of GAI chatbots on consumer preferences as well as the competitive landscape of the grocery sector, it is imperative to reassess theoretical viewpoints. This re-evaluation is necessary to gain insight into how the convenience and personalization provided by GAI chatbots shape these dynamics.

6.2. Practical implications

The incorporation of GAI chatbots into digital platforms for grocery shopping yields noteworthy practical implications that augment the overall customer shopping experience. Developers of OGS systems may take advantage of the following recommendations to effectively establish indications pertaining to attitude and trust within the domain of GAI.

First, promoters can utilize GAI algorithms to produce tailored recommendations for individual consumers. This feature can effectively demonstrate to consumers that the platform possesses a comprehensive understanding of their individual requirements and preferences, and is dedicated to delivering a satisfactory customer experience.

Second, companies can leverage GAI techniques to produce targeted content catered toward consumers. This information has the potential to educate viewers about various food categories, culinary techniques, and strategies for making nutritious dietary selections. This style of material has the potential to demonstrate to users that the platform serves as a valuable repository of knowledge and guidance.

Third, GAI can improve purchasing involvement and interactivity. Using GAI, virtual assistants may answer client questions about products or help them plan meals. This contact approach may build trust and a good relationship between users and the platform.

Fourth, ensure that users are consistently notified about routine enhancements and advancements in the functionality of the AI chatbot. Identify any progress in algorithms, novel functionalities, or enhancements that enhance the user experience. The pursuit of continuous development demonstrates a dedication to achieving excellence, which enhances user confidence in the chatbot's advancing capabilities.

Fifth, implement a feedback system that incentivizes users to report their experiences and suggestions. Proactively engage with user feedback by acknowledging problems and incorporating pertinent enhancements. Prompt and timely responses exemplify a customer-focused strategy, cultivating a favorable rapport and gradually establishing trust.

Sixth, facilitate the integration of the AI chatbot to provide smooth communication across many platforms, such as chat, voice, and social media. Ensuring a uniform and cohesive experience across several platforms improves accessibility and strengthens the dependability of the chatbot, thus increasing user confidence.

Seventh, integrate social proof features, such as user reviews and testimonials, into the chatbot interface. Positive comments from other users can function as a trust-building element, reassuring new consumers of the GAI chatbot's dependability and efficacy in the OGS process.

Finally, GAI could be a powerful tool for OGS platform developers. Developers can use GAI in a transparent and responsible way to create cues that convey attitude and build user trust. This could improve customers' purchase experiences by creating a more positive and interactive atmosphere.

6.3. Limitations and future scope

Several limitations of this study must be acknowledged. First, the study was conducted within a single country. Therefore, additional research is required to extend these findings' applicability to other countries and contexts. A second limitation in studying methods to enhance trust in OGS with GAI chatbots is the possible absence of applicability to various user demographics. User trust is a matter of personal opinion and can be shaped by individual inclinations, cultural discrepancies, and technology acquaintance. Consequently, research conducted in certain geographical areas or among specific population groups may not comprehensively encompass the many elements that generally influence trust. To overcome this constraint, future study can employ a cross-cultural and demographic-inclusive methodology to investigate the impact of cultural backgrounds and different levels of technology literacy on the efficacy of trust-building techniques with GAI chatbots.

Third, it is worth noting that the sample size may be deemed relatively small. Fourth, the analysis focused solely on two variables that were identified as drivers of attitude and trust. Fifth, it is vital to investigate the long-term effects and sustainability of trust-building interventions in the context of AI-driven OGS for future research. Although short-term studies may uncover immediate impacts, comprehending the long-term development of trust, particularly as consumers grow more acquainted with AI technologies, can yield useful insights. Sixth, exploring the impact of user education and awareness on establishing trust may be a promising approach. Subsequent investigations could further explore the ethical ramifications of AI-driven shopping experiences, scrutinizing consumer attitudes toward data privacy, algorithmic transparency, and the ethical utilization of AI in shaping purchasing choices. Researchers can contribute to the creation of comprehensive strategies for creating and maintaining trust in the changing field of OGS with GAI chatbots by addressing these factors.

Finally, it should be noted that all the data gathered in this study was obtained by self-reported scales, which introduces the possibility of measurement error and potential variability in the results. There are vast opportunities for future research in this domain. With the ongoing advancement of technology, it is foreseeable that the realm of shopping will undergo significant transformations, resulting in a heightened level of immersion and personalization. It is anticipated that GAI chatbots would exhibit enhanced intelligence capable of providing consumers with timely recommendations that are tailored to their dietary preferences, health objectives, and previous buying patterns. The growing prevalence of voice and NLP technologies enables users to engage with GAI chatbots more seamlessly, enhancing the convenience and effectiveness of OGS experiences.

7. Conclusion

The incorporation of GAI chatbots into OGS applications signifies a noteworthy advance in the domain of digital commerce. The utilization of AI-driven companions holds promise to fundamentally transform the grocery shopping experience because it introduces unprecedented levels of convenience, personalization, and efficiency. GAI chatbots play a crucial role in boosting the overall shopping experience by giving a range of services, including personalized product recommendations, shopping list management, real-time inventory updates, and improved customer support.

Furthermore, the potential for future advancements in this technology encompasses even more advanced capabilities, such as the implementation of voice recognition, the utilization of artificial intelligence for optimizing supply chain processes, and seamless connection with intelligent household products. As technology continues to progress, GAI chatbots are expected to become essential tools that not only optimize the grocery shopping procedure but also provide valuable insights to retailers, thereby creating a mutually beneficial situation for both consumers and businesses within this progressively digitalized environment.

CRediT authorship contribution statement

Debarun Chakraborty: Writing – original draft, Software, Methodology, Formal analysis, Conceptualization. **Arpan Kumar Kar:** Visualization, Validation, Software, Methodology, Conceptualization. **Smruti Patre:** Writing – original draft, Visualization, Formal analysis, Data curation. **Shivam Gupta:** Writing – review & editing, Supervision, Resources, Project administration.

Declaration of competing interest

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

Appendix A. . Interview questions for qualitative analysis

Interview Guide
Generic Questions

a) General discussion about firm and industry.
b) General discussion about respondents' profile, experience in buying the products.

Initial Interview Guide

a) Briefly present your level of understanding of generative artificial intelligence (AI)?
b) Could you please narrate how generative AI has changed the way you see the processes in your daily life?
c) What motivated you to shift/transform towards generative AI?

Final Interview Guide

a) What are some important factors for successful adoption of generative AI in OGS context?
b) To what extent value additions/economic/financial outcomes do you have gained with using generative AI?
c) What do you suggest for successful adoption of generative AI in OGS context?
d) Please elaborate on the challenges that you face for adopting generative AI?
e) What transformative trends you could perceive in online grocery industry?
f) Do you think the industry ready to accept the change?
g) What factors could help to mitigate the risks evolved due to the transformative trends?

Appendix B. . Themes extracted from interview excerpts

S. No.	Dimension	Interview excerpts
1	Perceived Interaction Quality	*I find the utilisation of the chatbot for assistance with my online grocery shopping to be really favourable. The process of locating information on the website is significantly expedited and simplified when compared to attempting to do so alone. The chatbot demonstrates a high level of proficiency in comprehending inquiries posed by users, particularly in instances where the queries lack specificity.* *I consistently exhibit reluctance in utilising chatbots; nonetheless, I experienced a positive outcome when interacting with the chatbot on the online grocery shop platform. The system demonstrated a high level of proficiency in promptly and accurately addressing all of my inquiries. Furthermore, it facilitated the discovery of previously unfamiliar products.*
2	Perceived Credibility	*I possess a certain degree of scepticism towards chatbots in a broad sense; nevertheless, I am open to the idea of experimenting with the chatbot featured on the online grocery shop platform. The user expresses a desire for the information to possess qualities of reliability and accuracy.*

(*continued on next page*)

(*continued*)

S. No.	Dimension	Interview excerpts
		I am uncertain about my stance about the utilisation of a chatbot for the purpose of conducting my online grocery shopping. I am concerned about the potential for the system to have difficulty comprehending my requirements or to potentially generate errors. *I am inclined to utilise the chatbot available on the online grocery store; but, I will exercise caution by verifying the accuracy of the information provided.*
3	Perceived Inertia	*I own a certain degree of reluctance in regards to engaging with the chatbot included on the online platform for online grocery shopping. The user expresses uncertainty on the functionality of the subject matter and expresses concern about potential difficulties associated with its usage.* *I am uncertain about my preparedness to utilise a chatbot for the purpose of conducting my supermarket shopping. I derive satisfaction from the ability to peruse the aisles and visually inspect the things first-hand.* *I have reservations with the utilisation of a chatbot for the purpose of conducting my food shopping. I am concerned about the potential occurrence of errors, as I aim to avoid acquiring incorrect products.*
4	Perceived Threat	*I have some concerns regarding the safeguarding of my personal information when utilising the chatbot feature for online grocery platform. I am concerned about the potential unauthorised access and misuse of my data.* *I possess a certain degree of scepticism regarding the reliability and credibility of the chatbot employed by the online grocery platform. I am concerned about the potential presence of bias or inaccuracies within the text.* *I am uncertain about the operational mechanisms of the chatbot employed by the online grocery platform. I have concerns regarding the potential capability of tracking my internet activities and the possibility of being subjected to targeted advertising for unnecessary products.* *I am uncertain about the extent of my agency in governing the chatbot functionality within the online grocery store. I am concerned that it may autonomously make decisions on my behalf without soliciting my opinion.*
5	Perceived Regret Avoidance	*I am uncertain about my inclination to experiment with the chatbot feature offered by the online grocery store. I am concerned about the potential for regret in the event of unsatisfactory outcomes.* *I possess some reservations regarding the utilisation of the chatbot feature on the online grocery platform. I am concerned about the possibility of committing an error and then selecting an incorrect item throughout the ordering process.* *I have reservations regarding the reliability of the chatbot employed by the online grocery platform. I am concerned about the possibility of making an error that could result in the acquisition of incorrect merchandise.* *I am uncertain about the potential value of engaging with the chatbot on the online grocery store, as there may be associated risks. I am concerned about the potential for regret in the event that the utilisation of the item or service does not yield favourable outcomes.*
6	Perceived Attitude towards Generative AI Chatbots	*In my opinion, the implementation of a chatbot on the online grocery store platform is a commendable concept. The ability to inquire and receive responses promptly, without the need for extended waiting periods or direct interaction with a person representative, is highly advantageous.* *I am highly satisfied with the chatbot featured on the e-commerce platform for supermarket shopping. The chatbot has a high level of responsiveness and helpfulness, surpassing the performance of other chatbots I have previously interacted with. Additionally, it demonstrates a superior ability to comprehend and address my inquiries.* *In my opinion, the implementation of a chatbot on the online grocery store platform is a promising avenue for enhancing the overall client experience. Utilising this feature significantly expedites the search process and enhances convenience compared to manually navigating around the website. Moreover, it is highly advantageous in obtaining prompt responses to inquiries pertaining to various items or services.* *The chatbot implemented on the online grocery store serves as a noteworthy illustration of how technology may be leveraged to enhance our daily existence. The implementation of this technology has facilitated and enhanced my grocery shopping experience, rendering it more convenient and enjoyable.*
7	Perceived Trust towards OGS using Generative AI chatbots	*I have confidence in the chatbot employed by the online grocery store to furnish me with precise responses to my inquiries and offer valuable suggestions. I possess a strong belief that the entity in question is exercising responsible utilisation of my data and refraining from engaging in the practise of selling it to advertisers who are external to the organisation.* *I am at ease utilising the chatbot feature on the online grocery store platform for the purpose of placing orders. The user expresses confidence in the security of their personal information and the accurate processing of their orders.* *I possess a sense of assurance in the chatbot's actions on the online grocery store, since I believe it is functioning in a manner that prioritises my welfare. I am aware that the intention is not to promote unnecessary purchases or exploit me.* *I have confidence in the reliability and consistency of the chatbot employed by the online grocery store. I am aware that the resource in question will be available to assist me whenever required, and that it will offer a reliable and uniform user experience.*
8	Perceived Anthropomorphism	*I place my confidence in the chatbot used by the online grocery store, as I believe it possesses the ability to furnish me with accurate responses to my inquiries and offer valuable suggestions. I possess a strong belief in the responsible use of my data by the entity in question, with the assurance that it will not be disseminated to third-party advertising for commercial purposes.* *I am at ease utilising the chatbot feature on the online grocery store platform for the purpose of placing orders. The user expresses confidence in the security of their personal information and the accurate processing of their orders.* *I have confidence in the chatbot employed by the online grocery store to exhibit honesty and transparency in its interactions with me. It is understood that in the event of any issues pertaining to my order, the chatbot possesses the capability to assist me in resolving them.* *I possess a sense of assurance in the notion that the chatbot employed by the internet grocery store is operating with a primary focus on promoting my utmost welfare. I am aware that the intention is not to promote unnecessary purchases or exploit my vulnerability.*

Appendix C. . Questionnaire with sources

Factors	Statements	Source
Perceived Interaction Quality(PIQ)	I perceive that the Interaction with generative AI chatbots offers sufficient information which facilitates online shopping of grocery items. I perceive that generative AI chatbots enables bi-directional communication which helps in buying grocery in online mode. I perceive that ease in interaction with generative AI chatbots facilitates online shopping of grocery items. I perceive that generative AI chatbots has friendly interface to effectively address my needs which shopping grocery items in online mode.	(Pelau, Dabija, & Ene, 2021)

(*continued on next page*)

(*continued*)

Factors	Statements	Source
Perceived Credibility(PCI)	I can rely on generative AI chatbots to help me to do online grocery shopping. I can trust generative AI chatbots to provide accurate information related to online grocery shopping I feel generative AI chatbots are knowledgeable in the domain of Online grocery shopping	(Chung & Han, 2017)
Perceived Inertia(PEI)	I will continue to do online grocery shopping without trying generative AI chatbots as I think using it will be more stressful to make changes. I will continue to shop grocery online without trying generative AI chatbots as I enjoy the present ways of shopping grocery online. I will continue to shop grocery online without trying generative AI chatbots as I always it the same way.	(Hsieh & Lin, 2018)
Perceived Threat(PET)	I fear that I may lose control over the way I shop grocery online if I will start using generative AI chatbots. I fear the uncertainty, confidentiality and security aspects of using generative AI chatbots for doing online grocery shopping. Overall, I consider it risky to adopt generative AI chatbots for doing online grocery shopping.	(Balakrishnan et al., 2021)
Perceived Regret Avoidance(PRA)	I will regret for choosing generative AI based Voice Assistants for shopping grocery online. I will feel more regret for bad outcomes that are the consequences of using generative AI chatbots to facilitate online grocery shopping. I prioritize avoiding regret over seeking new opportunities, even if the new opportunities of using generative AI chatbots for online grocery shopping look promising.	(Tsiros & Mittal, 2000)
Perceived Attitude towards Generative AI Chatbots(PAI)	I feel I will like using generative AI chatbots to shop grocery items through online. I feel I will feel good about using generative AI chatbots to shop grocery items through online. Overall I feel my attitude towards shopping grocery online with the help of generative AI chatbots is favourable.	(Balakrishnan et al., 2021)
Perceived Trust towards OGS using Generative AI Chatbots(PTT)	I believe products bought through online grocery platforms using generative AI chatbots will be of my interests I believe products brought through online grocery platforms using generative AI chatbots will be as per my needs I believe generative AI chatbots will treat me with respect and dignity while shopping online the grocery products	(Chakraborty et al., 2023; Wamba et al., 2023)
Anthropomorphism(ANT)	I feel generative AI chatbots are friendly while shopping online the grocery items. I feel generative AI chatbots are agreeable while shopping online the grocery items. I feel generative AI chatbots are sociable while shopping online the grocery items	(Munnukka et al., 2022)

References

Aghakhani, N., Oh, O., Gregg, D. G., & Karimi, J. (2021). Online review consistency matters: An elaboration likelihood model perspective. *Information Systems Frontiers, 23*, 1287–1301. https://doi.org/10.1007/s10796-020-10030-7

Alimamy, S., & Kuhail, M. A. (2023). I will be with you Alexa! The impact of intelligent virtual assistant's authenticity and personalization on user reusage intentions. *Computers in Human Behavior, 143*, Article 107711. https://doi.org/10.1016/j.chb.2023.107711

Ashaari, M. A., Singh, K. S. D., Abbasi, G. A., Amran, A., & Liebana-Cabanillas, F. J. (2021). Big data analytics capability for improved performance of higher education institutions in the Era of IR 4.0: A multi-analytical SEM & ANN perspective. *Technological Forecasting and Social Change, 173*, Article 121119.

Balakrishnan, J., Abed, S. S., & Jones, P. (2022). The role of meta-UTAUT factors, perceived anthropomorphism, perceived intelligence, and social self-efficacy in chatbot-based services? *Technological Forecasting and Social Change, 180*, Article 121692.

Balakrishnan, J., Dwivedi, Y. K., Hughes, L., & Boy, F. (2021). Enablers and inhibitors of AI-powered voice assistants: A dual-factor approach by integrating the status quo bias and technology acceptance model. *Information Systems Frontiers, 1–22*. https://doi.org/10.1007/s10796-021-10203-y

Bawack, R. E., Wamba, S. F., & Carillo, K. D. A. (2021). Exploring the role of personality, trust, and privacy in customer experience performance during voice shopping: Evidence from SEM and fuzzy set qualitative comparative analysis. *International Journal of Information Management, 58*, Article 102309.

Benbasat, I., Gefen, D., & Pavlou, P. A. (2008). Trust in online environments. *Journal of Management Information Systems, 24*(4), 5–11.

Beynon-Davies, P. (2018). Characterizing business models for digital business through patterns. *International Journal of Electronic Commerce, 22*(1), 98–124.

Blut, M., Chowdhry, N., Mittal, V., & Brock, C. (2015). E-service quality: A meta-analytic review. *Journal of Retailing, 91*(4), 679–700.

Bygstad, B. (2010). Generative mechanisms for innovation in information infrastructures. *Information and organization, 20*(3–4), 156–168.

Bygstad, B. (2017). Generative innovation: A comparison of lightweight and heavyweight IT. *Journal of Information Technology, 32*(2), 180–193.

Chakraborty, D., Patre, S., & Tiwari, D. (2023). Metaverse mingle: Discovering dating intentions in metaverse. *Journal of Retailing and Consumer Services, 75*, Article 103509. https://doi.org/10.1016/j.jretconser.2023.103509

Cheffi, W., Zahir-ul-Hassan, M. K., Farooq, M. O., Baqrain, A., & Mansour, M. M. H. (2023). Ethical leadership, management control systems and circular economy in SMEs in an emerging economy, the UAE. *Journal of Business Research, 156*, Article 113513.

Chen, J. S., Le, T. T. Y., & Florence, D. (2021). Usability and responsiveness of artificial intelligence chatbot on online customer experience in e-retailing. *International Journal of Retail & Distribution Management, 49*(11), 1512–1531.

Chi, O. H., Denton, G., & Gursoy, D. (2020). Artificially intelligent device use in service delivery: A systematic review, synthesis, and research agenda. *Journal of Hospitality Marketing & Management, 29*(7), 757–786.

Chung, N., & Han, H. (2017). The relationship among tourists' persuasion, attachment and behavioral changes in social media. *Technological Forecasting and Social Change, 123*, 370–380. https://doi.org/10.1016/j.techfore.2016.09.005

Crolic, C., Thomaz, F., Hadi, R., & Stephen, A. T. (2022). Blame the bot: Anthropomorphism and anger in customer–chatbot interactions. *Journal of Marketing, 86*(1), 132–148. https://doi.org/10.1177/00222429211045687

Dawar, N., & Bendle, N. (2018). Marketing in the age of Alexa. *Harvard Business Review, 96*(3), 80–86.

Dinh, C. M., & Park, S. (2023). How to increase consumer intention to use Chatbots? An empirical analysis of hedonic and utilitarian motivations on social presence and the moderating effects of fear across generations. *Electronic Commerce Research, 1–41*. https://doi.org/10.1007/s10660-022-09662-5

Dwivedi, Y. K., Balakrishnan, J., Baabdullah, A. M., & Das, R. (2023). Do chatbots establish "humanness" in the customer purchase journey? An investigation through explanatory sequential design. Psychology & Marketing..

Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., & Wright, R. (2023). "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management, 71*, Article 102642.

Ford, J., Jain, V., Wadhwani, K., & Gupta, D. G. (2023). AI advertising: An overview and guidelines. *Journal of Business Research, 166*, Article 114124. https://doi.org/10.1016/j.jbusres.2023.114124

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of marketing research, 18*(1), 39–50.

Gangwar, H., Date, H., & Ramaswamy, R. (2015). Understanding determinants of cloud computing adoption using an integrated TAM-TOE model. *Journal of enterprise information management, 28*(1), 107–130.

Gong, X., Zhang, K. Z., Chen, C., Cheung, C. M., & Lee, M. K. (2020). Transition from web to mobile payment services: The triple effects of status quo inertia. *International Journal of Information Management, 50*, 310–324.

Hand, C., Dall'Olmo Riley, F., Harris, P., Singh, J., & Rettie, R. (2009). Online grocery shopping: The influence of situational factors. *European Journal of Marketing, 43*(9/10), 1205–1219.

Harms, P. D., White, J. V., & Fezzey, T. N. A. (2024). Dark clouds on the horizon: Dark personality traits and the frontiers of the entrepreneurial economy. *Journal of*

Business Research, 171, Article 114364. https://doi.org/10.1016/j.jbusres.2023.114364

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the academy of marketing science, 43*, 115–135.

Hsieh, P. J. (2015). Healthcare professionals' use of health clouds: Integrating technology acceptance and status quo bias perspectives. *International journal of medical informatics, 84*(7), 512–523. https://doi.org/10.1016/j.ijmedinf.2015.03.004

Hsieh, P. J., & Lin, W. S. (2018). Explaining resistance to system usage in the Pharma Cloud: A view of the dual-factor model. *Information & Management, 55*(1), 51–63. https://doi.org/10.1016/j.im.2017.03.008

Jarratt, D. G. (1996). A comparison of two alternative interviewing techniques used within an integrated research design: A case study in outshopping using semi-structured and non-directed interviewing techniques. *Marketing Intelligence & Planning, 14*(6), 6–15.

Jha, A. K., & Shah, S. (2021). Disconfirmation effect on online review credibility: An experimental analysis. *Decision Support Systems, 145*, Article 113519.

Kar, A. K. (2021). What affects usage satisfaction in mobile payments? Modelling user generated content to develop the "digital service usage satisfaction model". *Information Systems Frontiers, 23*, 1341–1361.

Kar, A. K., Varsha, P. S., & Rajan, S. (2023). Unravelling the impact of generative artificial intelligence (GAI) in industrial applications: A review of scientific and grey literature. *Global Journal of Flexible Systems Management, 24*, 659–689.

Kar, A. K., & Kushwaha, A. K. (2021). Facilitators and barriers of artificial intelligence adoption in business–Insights from opinions using big data analytics. *Information Systems Frontiers, 1–24*. https://doi.org/10.1007/s10796-021-10219-4

Kim, H. W., & Kankanhalli, A. (2009). Investigating user resistance to information systems implementation: A status quo bias perspective. *MIS Quarterly, 33*(3), 567–582.

Klein, K., & Martinez, L. F. (2022). The impact of anthropomorphism on customer satisfaction in chatbot commerce: An experimental study in the food sector. *Electronic commerce research, 1–37*. https://doi.org/10.1007/s10660-022-09562-8

Kumar, A., Salo, J., & Li, H. (2019). Stages of user engagement on social commerce platforms: Analysis with the navigational clickstream data. *International Journal of Electronic Commerce, 23*(2), 179–211.

Kushwaha, A. K., & Kar, A. K. (2021). MarkBot–a language model-driven chatbot for interactive marketing in post-modern world. *Information Systems Frontiers, 1–18*. https://doi.org/10.1007/s10796-021-10184-y

Kushwaha, A. K., Kumar, P., & Kar, A. K. (2021). What impacts customer experience for B2B enterprises on using AI-enabled chatbots? Insights from Big data analytics. *Industrial Marketing Management, 98*, 207–221. https://doi.org/10.1016/j.indmarman.2021.08.011

Lee, J. H., Hsu, C., & Silva, L. (2020). What lies beneath: Unraveling the generative mechanisms of smart technology and service design. *Journal of the Association for Information Systems, 21*(6), 1621–1643.

Lee, K., & Joshi, K. (2017). Examining the use of status quo bias perspective in IS research: Need for re-conceptualizing and incorporating biases. *Information Systems Journal, 27*(6), 733–752. https://doi.org/10.1111/isj.12118

McLean, G., Osei-Frimpong, K., & Barhorst, J. (2021). Alexa, do voice assistants influence consumer brand engagement? – Examining the role of AI powered voice assistants in influencing consumer brand engagement. *Journal of Business Research, 124*, 312–328.

Munnukka, J., Talvitie-Lamberg, K., & Maity, D. (2022). Anthropomorphism and social presence in Human-Virtual service assistant interactions: The role of dialog length and attitudes. *Computers in Human Behavior, 135*, Article 107343. https://doi.org/10.1016/j.chb.2022.107343

Nel, J., & Boshoff, C. (2020). Status quo bias and shoppers' mobile website purchasing resistance. *European Journal of Marketing, 54*(6), 1433–1466. https://doi.org/10.1108/EJM-02-2018-0144

Ooi, K. B., Tan, G. W. H., Al-Emran, M., Al-Sharafi, M. A., Capatina, A., Chakraborty, A., & Wong, L. W. (2023). The potential of generative artificial intelligence across disciplines: perspectives and future directions. *Journal of Computer Information Systems, 1–32*. https://doi.org/10.1080/08874417.2023.2261010

Palivela, H. (2021). Optimization of paraphrase generation and identification using language models in natural language processing. *International Journal of Information Management Data Insights, 1*(2), Article 100025.

Pappas, I. O., & Woodside, A. G. (2021). Fuzzy-set qualitative comparative analysis (fsQCA): Guidelines for research practice in information systems and marketing. *International Journal of Information Management, 58*, Article 102310.

Pappas, I. O., Papavlasopoulou, S., Mikalef, P., & Giannakos, M. N. (2020). Identifying the combinations of motivations and emotions for creating satisfied users in SNSs: An fsQCA approach. *International Journal of Information Management, 53*, Article 102128.

Patre, S., Chakraborty, D., Kar, A. K., Singu, H. B., & Tiwari, D. A. (2023). The role of enablers and barriers in the upskilling and reskilling of users through professional skilling programs on EdTech platforms. *IEEE Transactions on Engineering Management*. https://doi.org/10.1109/TEM.2023.3328261

Pavlou, P. A., & Fygenson, M. (2006). Understanding and predicting electronic commerce adoption: An extension of the theory of planned behavior. *MIS Quarterly, 30*(1), 115–143.

Pelau, C., Dabija, D. C., & Ene, I. (2021). What makes an AI device human-like? The role of interaction quality, empathy and perceived psychological anthropomorphic characteristics in the acceptance of artificial intelligence in the service industry. *Computers in Human Behavior, 122*, Article 106855.

Pillai, S. G., Kim, W. G., Haldorai, K., & Kim, H. S. (2022). Online food delivery services and consumers' purchase intention: Integration of theory of planned behavior, theory of perceived risk, and the elaboration likelihood model. *International Journal of hospitality management, 105*, Article 103275. https://doi.org/10.1016/j.ijhm.2022.103275

Polisetty, A., Chakraborty, D., Kar, A. K., & Pahari, S. (2023). What determines AI adoption in companies? Mixed-method evidence. *Journal of Computer Information Systems*, 1–18.

Prasad Agrawal, K. (2023). Towards adoption of Generative AI in organizational settings. *Journal of Computer Information Systems, 1–16*. https://doi.org/10.1080/08874417.2023.2240744

Ramus, K., & Asger Nielsen, N. (2005). Online grocery retailing: What do consumers think? *Internet research, 15*(3), 335–352.

Rhee, C. E., & Choi, J. (2020). Effects of personalization and social role in voice shopping: An experimental study on product recommendation by a conversational voice agent. *Computers in Human Behavior, 109*, Article 106359. https://doi.org/10.1016/j.chb.2020.106359

Samuelson, W., & Zeckhauser, R. (1988). Status quo bias in decision making. *Journal of risk and uncertainty, 1*, 7–59. https://doi.org/10.1007/BF00055564

Schneider, B., Wheeler, J. K., & Cox, J. F. (1992). A passion for service: Using content analysis to explicate service climate themes. *Journal of applied psychology, 77*(5), 705.

Shahab, M. H., Ghazali, E., & Mohtar, M. (2021). The role of elaboration likelihood model in consumer behaviour research and its extension to new technologies: A review and future research agenda. *International Journal of Consumer Studies, 45*(4), 664–689.

Shin, D. (2020). How do users interact with algorithm recommender systems? The interaction of users, algorithms, and performance. *Computers in human behavior, 109*, Article 106344.

Shirish, A., & Batuekueno, L. (2021). Technology renewal, user resistance, user adoption: Status quo bias theory revisited. *Journal of Organizational Change Management, 34*(5), 874–893. https://doi.org/10.1108/JOCM-10-2020-0332

Simms, K. (2019). How voice assistants could change the way we shop. *Harvard Business Review, may*, 2–7.

Singh, R. (2019). Why do online grocery shoppers switch or stay? An exploratory analysis of consumers' response to online grocery shopping experience. *International Journal of Retail & Distribution Management, 47*(12), 1300–1317. https://doi.org/10.1108/IJRDM-10-2018-0224

Singh, R. (2022). "Hey Alexa–order groceries for me"–the effect of consumer–VAI emotional attachment on satisfaction and repurchase intention. *European Journal of Marketing, 56*(6), 1684–1720. https://doi.org/10.1108/EJM-12-2019-0942

Singh, R., & Söderlund, M. (2020). Extending the experience construct: An examination of online grocery shopping. *European Journal of Marketing, 54*(10), 2419–2446.

Srivastava, M., & Saini, G. K. (2022). A bibliometric analysis of the elaboration likelihood model (ELM). *Journal of Consumer Marketing, 39*(7), 726–743. https://doi.org/10.1108/JCM-12-2021-5049

Sohn, K., Sung, C. E., Koo, G., & Kwon, O. (2020). Artificial intelligence in the fashion industry: Consumer responses to generative adversarial network (GAN) technology. *International Journal of Retail & Distribution Management, 49*(1), 61–80.

Stahl, B. C., & Eke, D. (2024). The ethics of ChatGPT–Exploring the ethical issues of an emerging technology. *International Journal of Information Management, 74*, Article 102700.

Statista. (2022). Number of digital voice assistants in use worldwide from 2019 to 2024 (in billions).https://www.statista.com/statistics/973815/worldwide-digital-voice-assistant-in-use/.

Statista (2023). Total retail e-commerce revenue worldwide in 2022, by region (in billion U.S. dollars). https://www.statista.com/forecasts/1117851/worldwide-e-commerce-revenue-by-region.

Sun, Y., Chen, J., & Sundar, S. S. (2024). Chatbot ads with a human touch: A test of anthropomorphism, interactivity, and narrativity. *Journal of Business Research, 172*, Article 114403. https://doi.org/10.1016/j.jbusres.2023.114403

Tsai, J. M., Cheng, M. J., Tsai, H. H., Hung, S. W., & Chen, Y. L. (2019). Acceptance and resistance of tele-health: The perspective of dual-factor concepts in technology adoption. *International Journal of Information Management, 49*, 34–44.

Tsiros, M., & Mittal, V. (2000). Regret: A model of its antecedents and consequences in consumer decision making. *Journal of Consumer Research, 26*(4), 401–417. https://doi.org/10.1086/209571

Turner, S. F., Cardinal, L. B., & Burton, R. M. (2017). Research design for mixed methods: A triangulation-based framework and roadmap. *Organizational Research Methods, 20*(2), 243–267.

Van Droogenbroeck, E., & Van Hove, L. (2017). Adoption of online grocery shopping: Personal or household characteristics? *Journal of Internet Commerce, 16*(3), 255–286.

Venkatesh, V., Brown, S. A., & Bala, H. (2013). Bridging the qualitative-quantitative divide: Guidelines for conducting mixed methods research in information systems. *MIS quarterly*, 21–54.

Wamba, S. F., Queiroz, M. M., Jabbour, C. J. C., & Shi, C. V. (2023). Are both generative AI and ChatGPT game changers for 21st-Century operations and supply chain excellence? *International Journal of Production Economics, 265*, Article 109015.

Yang, R., & Wibowo, S. (2022). User trust in artificial intelligence: A comprehensive conceptual framework. *Electronic Markets, 32*(4), 2053–2077.

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.

Yu, L., Li, H., He, W., Wang, F. K., & Jiao, S. (2020). A meta-analysis to explore privacy cognition and information disclosure of internet users. *International Journal of Information Management, 51*, Article 102015.

Zhang, X., Guo, X., Wu, Y., Lai, K. H., & Vogel, D. (2017). Exploring the inhibitors of online health service use intention: A status quo bias perspective. *Information & Management, 54*(8), 987–997. https://doi.org/10.1016/j.im.2017.02.001

Debarun Chakraborty (Ph.D.) is an Associate Professor in Marketing at the Symbiosis Institute of Business Management (SIBM – Nagpur), Symbiosis International University in India. His research interests lie in the domain of Consumer Behaviour, Rural Marketing and Advertising & Sales Promotion. He has published several research papers in reputed journals like Journal of Business Research, IEEE TEM, Technovation, Psychology & Marketing, Journal of Retailing & Consumer Services and many more.

Arpan Kumar Kar (Ph.D.) is full Professor and a Chair Professor in Information Systems in Indian Institute of Technology Delhi, India. He works in the adoption, usage and user experience of emerging ICTs, using computationally intensive methods. He has authored over 220 papers and edited 10 books, of which over 80 publications are in ABDC A, ABS 3 and WoS Q1 level journals, and 15 are A* publications. As of January 2024, he has an H index of 53 and over 13,000 citations. He is the Editor in Chief of International Journal of Information Management Data Insights, which is a Q1 journal published by Elsevier. He is a Senior Editor for Decision Support Systems (ABDC A*). He is also an Associate Editor for International Journal of Information Management (ABDC A*), Communications of the Association for Information Systems (ABDC A), Journal of Computer Information Systems (ABDC A) and Global Journal of Flexible Systems Management (ABDC A). He has been a Guest Editor for reputed journals like Journal of the Association for Information Systems (A*, SSB), Decision Support Systems (A*), Industrial Marketing Management (A*), International Journal of Information Management (A*, 2 SIs), Information Systems Frontiers (A, 2 SIs), Electronics Commerce Research (A). He received the Research Excellence Award by Clarivate Analytics for highest individual Web of Science citations from 2015-2020 in India. He received the BK Birla Distinguished Researcher Award based on the count of ABDC A*/ABS 4 level publications between 2014 - 2019 in India. He is the recipient of the Best Seller Award from Ivey / Harvard in 2020 for the 5 year sales of his authored case study. In total, he has recieved over 20 national and international awards including 8 best paper awards from ACM, IFIP and IEEE conferences.

Smruti Patre (Ph.D.) is an Assistant Professor in Marketing at the Symbiosis Institute of Business Management (SIBM – Nagpur), Symbiosis International University in India. Her research has been published in journals of international repute namely Journal of Retailing & Consumers Services, IEEE TEM etc.

Shivam Gupta (Ph.D.) is a Professor at NEOMA Business School in France, with a strong track record in higher education. He is specialised in Statistics, Cloud Computing, Big Data Analytics, Artificial Intelligence and Sustainability. He has previously worked at Montpellier Business School, France and has a PhD, focusing on Cloud Computing and Operations Management from Indian Institute of Technology (IIT) Kanpur, India. He pursued his postdoctoral research at Freie Universität Berlin, Germany and SUSTech, China. He completed his HDR (accreditation to direct academic research) from University of Montpellier, France. He has published several research papers in reputed international journals.