Heliyon 10 (2024) e25031

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

Investigating the acceptance intentions of online shopping assistants in E-commerce interactions: Mediating role of trust and effects of consumer demographics

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A R T I C L E I N F O

Keywords:
Online shopping assistant
Conversational commerce
E-commerce
TAM
Acceptance
Intention to use

A B S T R A C T

Online shopping has various advantages, such as convenience, easy access to information, a greater variety of products or services, discounts, and lower prices. However, the absence of salespeople's personalized assistance decreases the online customer experience. Business-to-consumer e-commerce companies are increasingly implementing online shopping assistants (OSAs), interactive and automated tools used to assist customers without salespeople's assistance. However, no comprehensive model of OSA acceptance in e-commerce exists, including constructs from multiple information system disciplines, sociopsychology, and information security. This study aims to fill these gaps by empirically investigating consumers' intention to accept OSAs from a functional, social, relational, and security perspective. It identifies OSA acceptance factors in e-commerce through an extensive literature review and expert opinion. A research model is proposed after identifying structural relationships among the study's variables from the literature. The study employs partial least squares-structural equation modeling (PLS-SEM) to validate the proposed model empirically. The results indicate that anthropomorphism, attitude, ease of use, enjoyment, privacy, trust, and usefulness are crucial determinants of acceptance variables. There are significant moderating effects of respondents' gender and education on OSA acceptance. The study's results have substantial implications for academia, extending and validating the Technology Acceptance Model (TAM) for OSA acceptance in e-commerce. The study will help e-commerce marketers develop optimal adoption strategies when implementing OSAs on social media platforms.

1. Introduction

Algorithm-driven Online Shopping Assistants (OSAs) in e-commerce have existed for some time but have become more powerful and valuable due to the advancements in Artificial Intelligence (AI) [1]. Online assistants are applied in common e-commerce areas, such as ordering, delivering, and booking, to analyze customer data insights and personalize their experience. According to a report by Skyquest (2023), the global e-commerce market is estimated to be $62415 billion by 2030, rising at a cumulative growth rate of 11 % from 2023 to 2030. Business-to-consumer (B2C) e-commerce companies increasingly integrate chatbot OSAs to deliver better

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https://doi.org/10.1016/j.heliyon.2024.e25031
Received 31 July 2023; Received in revised form 27 December 2023; Accepted 18 January 2024
Available online 24 January 2024
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personalized and efficient shopping experiences to online consumers [2]. The American Marketing Association (AMA) states, "Online assistants (such as chatbots) are the future of marketing, and as they can be combined with social texting applications, they can replace online shopping applications" [156]. Van Euewen [3] categorized online assistants as "conversational commerce," originally termed by Messina [154] and described as "utilizing natural language interfaces, i.e., chat and voice, to interact with consumers, businesses, or services and bots." Juniper Research projects a growth of 58 % from 2021 to 2025 in total "conversational commerce" spending, reaching $290 billion by 2025 [4]. As per a report by Research and Markets [155], the global conversational commerce market is estimated to rise from USD 1740 billion in 2023 to $4915 billion by 2028. One of the primary reasons for the rise is the increasing innovation in the market due to advancements in AI; businesses are developing advanced conversational bots to provide quick and precise customer service and customized product/service suggestions.

Today, online assistants are revolutionizing the communication method of businesses and are increasingly embraced by them for consumer interaction [5]. Chatbots are new forms of online assistance that e-commerce businesses utilize to support customers while shopping [6,7]. Chatbots in online shopping increase operational efficiency and obtain cost savings for companies while providing convenience and responsiveness for consumers [8]. Digital assistants can delight customers by making customer conversations more effective, anticipating their needs based on preferences, interests, past purchase data, and queries, and delivering recommendations, offers, solutions, and answers [9]. While interacting with chatbots for customer service, consumers feel valued and enjoy the interactions [10]. Chatbots for online shopping offer various benefits, such as 24/7 availability, customer communication, automation, and personal assistance [1]. They promptly answer customer shopping-related queries in natural language [11]. Using their analytical skills, online agents, embodied on e-commerce platforms, make proactive and relevant product recommendations and expert product advice to customers [12]. Adopting OSAs enhances online customer experience [13] and leads to long-term customer relationships in online shopping [14].

Currently, OSAs are an essential part of customer conversations. Nevertheless, there is pushback from the customer side because they are not empathetic, lack human emotions, and do not show care when interacting with them [15]. Customers feel uncomfortable talking to these computer programs for purchase assistance and do not trust them with the product suggestions and payment reliability [16]. Since a large amount of customer data is collected and processed to respond to their requests, there is a risk of privacy and security breaches [17]. Hence, it is vital to study the factors that impact consumers' acceptance of OSAs to decrease customer pushback and help managers develop design strategies and increase use.

Despite their advantages, the factors that shape consumer acceptance of OSA are primarily unexplored [18]. In addition to the functional benefits of OSAs (such as enhanced shopping efficiency), they challenge psychological consumption motives and human-computer relationships by delegating tasks and decisions to technology. However, there is less research on human-computer interaction (HCI) factors of customer acceptance of OSAs in service interactions [7]. Despite being extensively used in the Indian e-commerce market, there are fewer empirical studies on Indian customers' acceptance of OSAs [19]. Most studies on OSA acceptance focus on individual aspects such as anthropomorphism [20]; there is a need to investigate other antecedents of willingness to accept. In addition, few studies have incorporated privacy risk as a barrier to conversational commerce acceptance in their research models [17].

Table 1
Summary of the literature review on OSA acceptance.

Author (s)	Objective	Technique	Findings
[18]	To determine the factors of customer adoption of intelligent voice assistants for shopping purposes.	Fuzzy set qualitative comparative analysis	Ease of use, usefulness, humanness, and social presence are essential predictors of customers' intention to adopt intelligent voice assistants.
[22]	To evaluate customer experience performance perception of AI-based voice assistants in e-commerce.	PLS-SEM	Consumer personality, trust, and perceived privacy play crucial roles.
[23]	To determine the usability and responsiveness of chatbots on online customer experience in e-commerce.	Covariance-based structural equation modeling (CB-SEM)	Customer trust factors are friendliness, empathy, task complexity, and identity disclosure.
[29]	To develop a chatbot trust model for customer service and enhanced customer experience in e-commerce.	PLS-SEM	Communication quality factors are credibility and competence; HCI factors are anthropomorphism, social presence, and media richness; and human use and gratification factors are informativeness and playfulness.
[25]	To determine the intention to use an online recommendation system in e-commerce.	PLS-SEM	Design factors are technology fear, perceived trust, "performance expectancy," "hedonic motivation," "effort expectancy," social influence, "perceived value" and habit.
[26]	To examine consumer trust, response, and acceptance of virtual assistants taking social roles.	Experiment	Social presence, technology error, anthropomorphic design cues, perceived competence, warmth, and data disclosure are acceptable factors.
[27]	Most chatbots deployed on e-commerce sites are machine-like and have a low usage rate. The objective of the study is to humanize the chatbots.	Experiment	Chatbots should be anthropomorphic: have a human-like visual appearance and human-like identity and engage in human-like conversations (i.e., interactive messages).
[28]	To determine the acceptance of AI devices in service delivery.	CB-SEM	Significant factors are social influence, hedonic motivation, anthropomorphism, performance expectancy, and emotions.
[21]	To develop a service and technology integration willingness scale in retail.	CB-SEM	Dimensions of consumer intention to adopt are performance efficacy, enjoyment, anthropomorphism, social influence, and emotions.

Hence, a comprehensive model must be developed, including constructs from multiple information systems disciplines, socio-psychology, and information security. This study aims to fill these gaps by empirically investigating consumers' intention to accept OSAs from a functional, social, relational, and privacy perspective. Hence, the study answers the research question.

Research Question 1. What are the most critical factors of consumer acceptance of OSA in e-commerce interactions?

Customer intention to accept a service technology varies across demographic groups [21]. Hence, marketers need to customize their application of an OSA according to customer groups. This study aims to determine the moderating effects of consumer demographic characteristics on their intention to accept OSAs. Therefore, the study answers the research question below.

Research Question 2. Do gender, age, education, and income consumers significantly moderate their acceptance of OSAs in e-commerce interactions?

The structure of the remainder of this article is as follows. Section 2 presents the proposed research model and hypothesis development. The questionnaire development, data collection, and data analysis technique are detailed in Section 3 of the methodology. The findings are shown in Section 4, the discussion is in Section 5, and the implications and conclusion are in Section 6.

2. Research framework and hypothesis development

2.1. Acceptance of online shopping assistants (OSAs)

Table 1 summarizes the literature review on consumer acceptance of OSAs. The findings indicate that existing research has investigated consumer trust in such technologies [22–26]. Past studies have explored a few variables of acceptance, such as anthropomorphism [21,24,26–28], performance expectancy [21,22,25,28], social presence [18,24,26], social influence [21,25,28], and emotions [21,28]. There is less research on the effect of privacy on the acceptance of digital assistants in e-commerce [22]. Moreover, very few studies have employed the popular TAM constructs "perceived usefulness" and "perceived ease of use" to determine OSA acceptance.

2.2. Technology acceptance model (TAM)

This research chooses the Technology Acceptance Model (TAM), introduced by Davis [30], as the base model because it is one of the most robust frameworks for studying consumers' acceptance of a new technology [31]. TAM is more powerful and favored than other technology acceptance models in adopting the Internet and mobile-based technologies due to its higher explanatory power [32,33]. Past studies have applied the TAM to study consumers' adoption in different contexts, such as mobile internet [34], mobile commerce [35], augmented reality mobile apps in shopping [36], virtual reality devices [37], and intelligent information technology in digital transformation [38]. This study extends the original TAM by adding other functional, social, relational, and privacy constructs to examine OSA acceptance in e-commerce and validate the proposed model.

2.3. Determinants of OSA acceptance: an extended TAM

The study adopts a two-stage approach to identify the factors of OSA acceptance, extensive literature review, and expert opinion to evaluate the situation from both literature and specialist perspectives and provide better insight. In the first stage, the study extensively reviews the literature related to OSA in e-commerce. In the second stage, expert opinions from academia and industry are gathered to

Table 2
The factors of OSA acceptance in e-commerce.

Dimensions	Factors (Code)	Description	Supporting references
Functional	Usefulness (USF)	Consumers are motivated to use OSAs if they provide valuable benefits such as convenient and efficient shopping, accurate product information, and reliable recommendations.	[11,30,39–42]
	Ease of use (EAS)	Consumers develop a positive attitude if OSAs are noncomplex and effortless.	[21,30,41]
	Performance (PER)	Consumers adopt OSAs if they provide fast, reliable, accurate, consistent, and quality services.	[21,28,43]
Social	Social influence (SNI)	Consumers are more likely to adopt OSAs if they align with their social group norms, increasing their sense of belongingness and social identity.	[28,42,44,45]
	Social presence (SOP)	People are willing to interact with OSAs if there is a sense of coexistence with another human being.	[44,46,47]
	Sociability (SOC)	People prefer OSAs with social abilities like interactive communication and social cognition.	[44,48–50]
	Anthropomorphism (ANT)	Consumers like to interact with OSAs with human-like physical and psychological characteristics such as their design, appearance, consciousness, and mind.	[21,47,51–53]
Relational	Rapport (RAP)	Individuals desire friendliness and understanding from OSAs during a service interaction.	[44,54,55]
	Enjoyment (ENJ)	Entertainment, fun, and pleasure from OSA service interaction motivate users to adopt it.	[11,28]
	Trust (TRU)	People's trust in OSAs is their confidence in their competence, credibility, reliability, and accuracy.	[46,54,55]
Barriers	Privacy risk (PRI)	Perceived privacy concerns, such as the safety of personal information and security vulnerabilities, inhibit the intention to use OSAs.	[11,42,48,56]
	Anxiety (ANX)	Individuals are anxious to use OSAs because they fear service failure and distrust in performance.	[41,49,57]

screen and verify the factors identified from the literature review. This approach resulted in a selection of twelve elements of OSA acceptance in e-commerce, described in Table 2.

2.3.1. Usefulness

The TAM, proposed by Davis, assumes usefulness as a core antecedent of technology acceptance [30]. Perceived usefulness is "the degree to which people believe a technology usage will increase their task performance" [30]. The extended TAM studies also conclude that usefulness is most important for technology acceptance [58]. Empirical evidence exists for a positive relationship between usefulness and acceptance of a service innovation in retail [59]. Usefulness predicts customers' intention to accept intelligent voice assistants for shopping [18] and AI fashion chatbots in services [60]. Perceived usefulness helps overcome consumer resistance to the sustainable adoption of chatbot services [61].

Perceived usefulness helps understand the attitude and intention to use mobile shopping in retail [62] and mobile payment [63]. Usefulness affects consumers' attitudes towards online shopping [64] and chatbot technology in online shopping [3]. Usefulness influences the attitude and acceptance of smartphone chatbots in mobile shopping [1]. Perceived usefulness affects the attitude and acceptance of voice-based digital assistants [65].

Perceived usefulness affects trust in mobile shopping applications [62]. Perceived usefulness has a considerable impact on trust in interaction with an AI chatbot [7], intelligent voice assistants for shopping purposes [18], fashion chatbots' product recommendation services [66], and voice-based digital assistants [65]. The authors propose the following hypotheses.

H1a. Usefulness significantly and positively affects consumer trust in OSA in e-commerce interactions.

H1b. Usefulness significantly and positively affects attitude toward OSA in e-commerce interactions.

H1c. Usefulness significantly and positively impacts the acceptance of OSA in e-commerce interactions.

2.3.2. Ease of use

Ease of use is another essential element of the TAM and is "the degree to which an individual believes that using a technology will be free of effort" [30]. Perceived ease of use influences customer intention to use the Internet for grocery shopping [67] and intelligent voice assistants for shopping purposes [18]. Perceived ease of use affects customer acceptance of AI fashion chatbot services [60]. Perceived ease of use affects attitude and intention to use smartphone chatbots for shopping [1] and mobile shopping assistants [68].

Ease of use is a vital predictor of a person's attitude toward a customer service assistant [21] and an AI assistant [41]. Perceived ease of use is significant in customers' attitudes toward the implementation of AI in fashion [41], smartphone chatbots for shopping [1], digital technology in unorganized retail [69], e-service delivery [70], and mobile shopping apps [71].

Past studies suggest that ease of use impacts trust in mobile payment [72], online purchasing [73], online shopping chatbots [1], AI chatbots for communication [74], and AI service delivery robots [75]. Recent research highlights the importance of offering easy-to-use and trustworthy conversational agents for online shopping [8]. The authors propose the following hypotheses.

H2a. Ease of use significantly and positively affects consumer trust in OSA in e-commerce interactions.

H2b. Ease of use significantly and positively affects consumer attitude toward OSA in e-commerce interactions.

H2c. Ease of use significantly and positively impacts consumer acceptance of OSA in e-commerce interactions.

2.3.3. Performance

If online assistants provide "fast, reliable, accurate, and consistent services," they enhance service quality, i.e., higher perceived performance [21]. Performance impacts the intention to adopt AI customer services in retail [48]. Higher certainty of shoppers' needs results in a higher perception of online assistants' performance, leading to higher acceptance and use of the technology [43]. A fashion chatbot's product recommendation service's perceived quality (i.e., performance) significantly affects customer response [66].

Performance expectancy impacts user attitude and acceptance of mobile shopping assistants [68]. Performance affects customer attitudes toward online shopping [76]. Perceived performance is significant in customer attitudes toward AI implementation in fashion [41]. Higher perceived performance generates positive customer emotions toward using intelligent devices for services [28].

Performance can be used to measure customers' trust in AI robots for service delivery [75]. Performance impacts customers' trust in mobile payment [77], quality of communication with fashion chatbots [66], and voice shopping [22]. Increasing the performance of intelligent customer service chatbots in e-commerce enhances customers' trust in them [78]. The authors propose the following hypotheses.

H3a. Performance significantly and positively affects consumer trust in OSA in e-commerce interactions.

H3b. Performance significantly and positively affects attitude toward OSA in e-commerce interactions.

H3c. Performance significantly and positively affects the acceptance of OSA in e-commerce interactions.

2.3.4. Social network influence

Social network influence is "a person's perception that people who are important to him think he should or should not use a system" [46]. Aligning with social group norms benefits the social identity of the consumer [28]. Social influence is crucial in evaluating the acceptance of AI assistants for services, especially when they do not have the ability and knowledge to assess their appropriateness

[45]. Social influence positively affects consumers' acceptance of automated technologies [44]. Symbolic benefits such as enhanced social status among peers motivate consumers to use AI-based technologies [42].

Social influence is a significant driver of customer attitude towards online shopping [79], socially assistive robots [80], and conversational agents [81]. Past research has tried to understand the impact of social influence on trust in online purchasing [73] and product recommendation assistants [82]. Based on the literature, the authors propose the following hypotheses.

H4a. Social networks significantly and positively influence trust in OSA in e-commerce interactions.

H4b. Social networks significantly and positively influence consumers' attitudes towards OSA in e-commerce interactions.

H4c. Social networks influence consumers' acceptance of OSA in e-commerce interactions significantly and positively.

2.3.5. Anthropomorphism

Anthropomorphic assistants have a human-like form [83]. Companies use OSAs with human-like communication skills to guide consumers with online shopping and customer service [51]. Anthropomorphism considerably impacts customers' purchases using chatbots [51]. Humanness is an essential predictor of customers' intention to accept intelligent voice assistants for shopping [18]. Anthropomorphism significantly enhances users' likelihood of complying with a virtual assistant's requests [84]. The anthropomorphism of an AI device, characterized by human-like interaction quality, empathy, and psychological traits, has a significant role in accepting AI in the service industry [85].

An anthropomorphic agent on a website increases a sense of social reality and produces favorable consumer attitudes and behavioral intentions [83]. Anthropomorphism impacts customer attitude and satisfaction with chatbots in e-commerce [20]. Anthropomorphic design cues influence attitude toward a conversational agent [81]. Anthropomorphism affects customers' trust in automated agents [86], intelligent voice assistant technologies [87], fashion shopping chatbots [88], e-commerce chatbots [29], and humanoid service robots [89]. The authors propose the following hypotheses.

H5a. Anthropomorphism significantly and positively affects trust in OSA in e-commerce interactions.

H5b. Anthropomorphism significantly and positively affects attitudes toward OSA in e-commerce interactions.

H5c. Anthropomorphism significantly and positively affects the acceptance of OSA in e-commerce interactions.

2.3.6. Social presence

Social presence is "the experience of sensing a social entity when interacting with a system" [46]. It includes "a sense of personal, sociable, and sensitive human contact" [90]. Social presence is an essential predictor of customers' intention to accept intelligent voice assistants for shopping [18]. Social presence enhances satisfaction with the services provided by OSAs, which positively affects consumers' intentions to use automated assistants [44]. The extent to which a user senses human presence when interacting with a technology determines its perception and acceptance [91]. Social presence has a vital role in the design of virtual agents in e-commerce [12] and customer intention to accept AI fashion chatbot services [60].

Social presence affects attitudes toward chatbots [92], innovative interactive services [93], millennials' attitudes toward chatbots in retail [94], and socially interactive robots [95]. Existing research suggests that social presence positively influences trust in chatbots in online purchasing [29] and interactions with chatbots [96]. Hence, the authors propose the following hypotheses.

H6a. Social presence significantly and positively affects consumer trust in OSA in e-commerce interactions.

H6b. Social presence significantly and positively affects attitudes toward OSA in e-commerce interactions.

H6c. Social presence significantly and positively affects the acceptance of OSA in e-commerce interactions.

2.3.7. Sociability

Sociability is "the ability of a system to perform sociable behavior" [46]. It is characterized by pleasant conversations, interaction, understanding, and excellent behavior [46]. Sociability influences the acceptance of virtual reality devices [37]. If intelligent agents display social abilities and interact socially, it motivates consumers to engage with them [44]. Perceived sociability influences users' intention to adopt online customer service agents in e-commerce [48]. Social ability impacts the choice to accept AI devices for services [85].

Perceived sociability affects attitudes towards socially interactive robots [95]. Social capability impacts customers' acceptance of retail service robots [49]. Regarding trust, sociability is used to design embodied virtual agents in e-commerce [12] and AI-enabled chatbots [97]. The authors propose the following hypotheses to enhance the existing body of knowledge on the impact of sociability on trust, attitude, and acceptance of OSA.

H7a. Sociability significantly and positively affects consumer trust in OSA in e-commerce interactions.

H7b. Sociability significantly and positively affects attitude toward OSA in e-commerce interactions.

H7c. Sociability significantly and positively affects the acceptance of OSA in e-commerce interactions.

2.3.8. Enjoyment

Enjoyment is "feelings of joy or pleasure associated with using a system" [46]. Past studies have investigated the influence of perceived enjoyment on acceptance of the mobile internet [34], mobile payment [98], chatbots for customer communication in retail [11], acceptance of virtual reality devices [37], customer intention to accept AI fashion chatbots in services [60], intention to use conversational agents by older adults [99], and consumer acceptance of chatbots [100].

Enjoyment influences the attitude and acceptance of mobile shopping [101], smartphone chatbots in mobile shopping [1], millennials' attitudes toward chatbots in retail [94], and socially interactive robots [95]. There is empirical evidence on the impact of perceived enjoyment on trust in smartphone chatbots for shopping [1], virtual assistants [102], product recommendation agents [82], and service robots [89]. The authors propose the hypotheses below.

H8a. Enjoyment significantly and positively affects consumer trust in OSA in e-commerce interactions.

H8b. Enjoyment significantly and positively affects attitude toward OSA in e-commerce interactions.

H8c. Enjoyment significantly and positively affects acceptance of OSA in e-commerce interactions.

2.3.9. Rapport

Rapport is characterized by a friendly relationship with a high degree of understanding, attention, positivity, coordination, and empathy [54]. Accepting a service technology depends on how much it can fulfill a consumer's need for rapport [55]. Many consumers still see services as needing personal contact; their sense of connection is vital for accepting automated technology in services [44]. Rapport, characterized by emotional reactions to users' feelings, impacts the intention to use AI devices for services [85].

Rapport expectation significantly influences attitudes toward AI voice assistants [42], social robots [54], AI chatbots [103], and digital voice assistants [104]. Rapport has an evolving role in trust in digital voice assistant technology in service encounters [44], AI-based service encounters [105], AI chatbots [103], and the trustworthiness of digital voice assistants [104]. The authors propose the following hypotheses.

H9a. Rapport significantly and positively affects consumer trust in OSA in e-commerce interactions.

H9b. Rapport significantly and positively affects attitude toward OSA in e-commerce interactions.

H9c. Rapport significantly and positively affects the acceptance of OSA in e-commerce interactions.

2.3.10. Privacy risk

Privacy concerns such as the safety of personal information and security vulnerabilities inhibit consumers' acceptance of a technology [42,48]. Voice assistants threaten users' privacy by continuously gathering details beyond their knowledge and control [42]. Privacy cynicism negatively influences customer acceptance of chatbots in online retailing [11], voice assistant technology [31], AI-based customer service in retail [48], use of personal shopping assistants [56], consumer experience performance during voice shopping [22], and user acceptance of voice-based digital assistants [65].

Privacy risk affects the attitude and acceptance of smartphone chatbots in mobile shopping [1]. Internet privacy is significantly related to user attitudes toward chat-based OSA technology [3]. Privacy concerns result in negative attitudes and less acceptance of voice assistants [31]. Past studies concluded that online privacy risks considerably affect customers' trust in voice shopping [22], mobile commerce acceptance [106], mobile payment usage [107], and complex electronic services adoption [108]. The authors propose the following hypotheses.

H10a. Privacy risk significantly and negatively affects consumer trust in OSA in e-commerce interactions.

H10b. Privacy risk significantly and negatively affects consumer attitudes toward OSA in e-commerce interactions.

H10c. Privacy risk significantly and negatively affects consumer attitudes toward OSA in e-commerce interactions.

2.3.11. Anxiety

Technology anxiety "evokes anxious or emotional reactions when using a system" [46]. Customers fear using technology if they fear service failure and payment fraud and thus distrust their performance [49,109]. Technology anxiety hinders purchase intention on the adoption of internet shopping [110], mobile shopping websites [111], customers' use of a personal shopping assistant [59], acceptance of shopping chatbots [57], and use of intelligent assistants for online shopping [41].

Anxiety influences customer attitudes toward mobile payment [77], retail service robots [49], and user attitudes toward AI digital assistants in services [112]. Past studies indicate that anxiety impacts customer trust in mobile payment [77], AI digital assistants [112], virtual shopping agents for older users [113], and retail and personal shopping assistants [59]. Based on the literature, the authors propose the following hypotheses.

H11a. Anxiety significantly and negatively affects consumer trust in OSA in e-commerce interactions.

H11b. Anxiety significantly and negatively affects attitude toward OSA in e-commerce interactions.

H11c. Anxiety significantly and negatively affects the acceptance of OSA in e-commerce interactions.

2.3.12. Trust

In a technology acceptance context, trust is the feeling that an e-commerce company cares about the well-being of its customers [22]. Trust is a person's view of the credibility and reliability of a service assistant [55]. Trust is crucial in an individual's decision-making approach to online purchases [114]. There is empirical evidence that trust affects the acceptance of fashion chatbots [66], AI devices [85], service assistants [115], and chatbots in online retailing [8].

Trust impacts attitudes toward chatbots for online shopping [1], attitudes toward recommendation agents [116], and customer attitudes in the e-commerce retailing sector [117]. A recent study on shopping with a voice assistant explored the mediating role of trust in consumer attitude and intention to use a voice assistant [19]. Hence, designing a trustworthy technology is essential. The study proposes that trust has a significant role in accepting and attitude toward OSA in e-commerce. The authors present the hypotheses below.

H12a. Trust significantly and positively affects attitudes toward OSA in e-commerce interactions.

H12b. Trust significantly and positively affects the acceptance of OSA in e-commerce interactions.

2.3.13. Attitude and acceptance

Attitude is "positive or negative feelings about the appliance of a technology" [46]. This study proposes attitude as a direct determinant of acceptance, defined as "consumers' behavioral intention to use an OSA" [118]. A recent study on the acceptance of smartphone chatbots for mobile commerce concluded that attitude considerably influences the intention to use chatbots for mobile shopping [1]. The original TAM and many further studies on consumer adoption have used attitude as a significant mediating variable between various consumer perception constructs and technology acceptance [115]. Based on the literature, the authors propose the following hypothesis.

H13. Attitude significantly and positively affects acceptance of OSA in e-commerce interactions.

2.3.14. Moderating variables

Existing research has used consumers' gender [1], age [115], education [119], and income [120] as determinants of technology acceptance in various contexts. Marketers extensively use these variables for market segmentation. Empirical evidence shows that consumers' gender, age, education, and income impact their online shopping behavior [121], attitude, and intention to use innovative technology such as internet baking in online retailing [122,123]. However, there is little to no research on the moderating impact of consumers' demographic details, such as gender, age, income, and education qualifications, on OSA technology acceptance. This research fills this gap by investigating the moderating effect of customers' gender, age, education, and income on trust, attitude, and intention to use OSAs in e-commerce. It is vital to study the effect of these demographic variables to formulate OSA acceptance strategies catering to each segment.

H14. Gender significantly moderates the relationships in H12 and H13.

H15. Age significantly moderates the relationships in H12 and H13.

H16. Education significantly moderates the relationships between H12 and H13.

H17. Income significantly moderates the relationships in H12 and H13.

3. Methodology

3.1. Questionnaire development

After identifying structural relationships among the factors selected, the study develops a structured survey questionnaire to measure OSA acceptance in e-commerce. The questionnaire has two parts: Section A collects the participants' demographic details, and Section B measures respondents' intentions to accept OSAs. The "item pool" about a variable is carefully selected, considering all content potentially related to the construct. The developed "item pool" is tested for content validity through a focus group discussion, and the items selected by at least three of the four groups are considered for further analysis in the study. The final questionnaire consists of 82 statements for the variables in the study, measured with a five-point *Likert Scale* (from 1 = strongly disagree to 5 = strongly agree) (refer to Appendix 2 for the complete questionnaire). The items in the questionnaire are adapted from the literature. The statements for usefulness, ease of use, rapport, anthropomorphism, social ability, privacy risk, and trust are adapted from Refs. [39,44,49,55], and [57]; performance and social influence from Refs. [21,28]; enjoyment and anxiety from Refs. [54,89]; and social presence from Ref. [27].

3.2. Sampling and data collection

Sampling was performed by choosing a significant number of participants from the study's target population to make inferences about the total population. Purposive sampling was used to determine the participants for the study. Participants' inclusion criteria are (i) frequent online shoppers and (ii) having interacted with an OSA at least once. The present study employs an online survey method to collect primary data. The participants were selected subjectively via contacts, acquaintances, and social media. Although convenience sampling was involved in this process, the inclusion criteria make this approach purposive [124,125]. We approached 400 participants for the study, and only 272 responses were received (a 68 % response rate). There was no missing data since it was an online survey with needed fields [126]. It should be stated that the authors were not required to obtain ethical committee approval for this study. The participants were informed that their responses would be used anonymously for this study; completing the questionnaire indicated consent to participate. The study employed PLS-SEM to test the hypotheses. According to Ref. [127], "the minimum sample size should be ten times the maximum number of arrowheads pointing at a latent construct in a PLS-SEM." Hence, the study's sample size is appropriate. PLS-SEM equips researchers to evaluate complex models with many variables and structural paths without applying the distribution requirements to the data [128].

3.3. Profile analysis of the respondents

Table 3 shows the demographic details of the participants. Of the 272 respondents received, 65.5 % were male, and 34.4 % were female. 41.3 % of the respondents were aged less than 35 years, while 58.6 % were 36 years and above; this shows the equal participation of the young and old age groups. 96.1 % of the respondents were graduates or above and faced no issues understanding the questionnaire. 86.7 % of the respondents were employed, including government employees, private employees, and self-employed individuals. 32.0 % of the respondents earned Rs. 50,000 or below per month, compared to 68.0 % of the participants making more than Rs. 50,000 per month. Also, 70 % of the respondents were married and 30 % were single.

3.4. PLS-SEM

The study used PLS-SEM to test the hypotheses. It is a commonly employed technique for analyzing causal associations between latent variables in various marketing areas, such as consumer research [129]. It is beneficial when the sample is small and nonnormal or has no outliers [130]. PLS-SEM provides findings with better reliability and validity than other multivariate software [131]. This technique is recommended if the complex research model has many variables and structural paths [128]. A multi-country study comparing CB-SEM and PLS-SEM concludes that item loadings, average variance extracted, and composite reliability are higher in PLS-SEM, indicating more construct reliability and validity [132]. The study employed the SmartPLS 4.0 tool to develop the structural model. SmartPLS is a helpful software for evaluating models in marketing research [133]. It is popular among researchers because it is freely available, is easy to use, and has advanced functions [134].

4. Results

4.1. Reliability and validity

The validity of the survey questionnaire is checked using convergent and discriminant validity. Convergent validity examines whether multiple statements of a construct represent that construct [119]. The outer loadings of all the items in the questionnaire are checked. The statements with external loading values less than 0.7 are removed from further evaluation, i.e., ACC2, ANT8, EAS4, ENJ1, ENJ5, PER4, PRI3, PRI4, RAP2, RAP4, SNI2, SOC3, SOC4, SOP4, SOP7, and USF1 (refer to Appendix A Table A1). Table 4 gives the reliability and convergent validity of the twelve factors identified in the study. The average variance extracted (AVE) is more than 0.50 for all the variables, complying with the Fornell and Larcker requirement [135]. Composite reliability (CR) is significant for all the

Table 3
The demographic details of the participants.

Demographic Characteristic	Category	Percent %
Gender	Male	65.5
	Female	34.4
Age	18–25 years	17.2
	26–35 years	24.1
	36–50 years	43.3
	51 years and above	15.3
Education	Under-graduate	3.9
	Graduate	14.3
	Post-graduate	38.9
	Above post-graduate	36.9
	Other	5.9
Occupation	Government Employee	49.3
	Private Employee	19.2
	Self-employed	4.9
	Unemployed	13.3
	Other Occupation	13.3
Average Monthly Income	Below Rs. 50,000	32.0
	Rs. 50,000–1,00,000	19.2
	Rs. 1,00,000–1,50,000	17.2
	Rs. 1,50,000–2,00,000	11.3
	Above Rs. 2,00,000	20.2
Marital Status	Married	70.0
	Single	30.0

variables with a cut-off value of 0.70 [136]. Moreover, Cronbach's alpha (α) for the variables is at least 0.70, which means the scale is reliable [137]. Hence, the outer model meets the requirements of construct reliability and concurrent validity. The discriminant validity is evaluated using the Heterotrait-Monotrait ratio (HTMT), Fornell and Larcker [135] criterion, and cross-loadings. Table 5 shows that the HTMT ratios are not more than 0.85, indicating excellent discriminant validity [138]. The correlation matrix (Table 6) highlights that all the factors' pairs correlate less than 0.70. The model's explained variance (R^2) is 70.6 % for the acceptance variable, 44.5 % for the attitude variable, and 35.5 % for the trust variable. The SRMR is 0.063, less than the cut-off of 0.08, indicating a perfect model fit [139]. Furthermore, NFI is 0.921, a good model fit per the Bentler & Bonett criteria [140].

4.2. Path estimates

The statistical significance of the hypotheses is checked using the consistent bootstrapping procedure with 5000 samples, the percentile bootstrap method, a two-tailed test, and a 95 % confidence interval in Smart PLS 4. Fig. 1 shows the model of OSA acceptance in e-commerce developed by authors using the results of the PLS-SEM. The model shows the significant hypotheses, significant (solid lines), and insignificant (dotted lines) effects.

Table 7 gives the path coefficients of PLS-SEM analysis. The analysis confirms that ANT → TRU has the most substantial effect with a path coefficient of 0.401 and 0.000 significance level, followed by ATT → ACC, TRU → ATT, and TRU → ACC, which also have a 0.000 significance level. Hypotheses USF → TRU, ANT → ATT, EAS → ACC, PRI → ACC, SOC → ATT, and SOC → ATT are accepted with 99 % confidence. Other supported effects are ANT → ACC, USF → ACC, SNI → ATT, ENJ → ACC, and USF → ATT at 95 % confidence. The results indicate that anthropomorphism, attitude, ease of use, enjoyment, privacy, trust, and usefulness directly impact OSA acceptance. Attitude mediates the effect of anthropomorphism, social network influence, social ability, trust, and usefulness on OSA acceptance. Meanwhile, trust mediates the effect of anthropomorphism and usefulness on OSA acceptance.

4.3. Moderation analysis with interaction effects

The study evaluates the moderating impact of respondents' demographics, i.e., gender, age, education, and income, on OSA acceptance in e-commerce. Moderation analysis is a way to explain heterogeneity in the data [127]. The moderating effect is tested by evaluating the "interaction term" (i.e., the product of the moderating and predictor variables), which signifies whether the changes in the moderating variable increase or decrease the power of the relationship. Table 8 shows that hypothesis EDU x TRU → ACC is firmly accepted by a significance of 0.01. A simple slope analysis reveals that the effect of trust leading to acceptance is more substantial for highly educated respondents (refer to Fig. 2). Hypothesis GEN x TRU → ACC is accepted weakly at 0.10 significance.

Further analysis (refer to Fig. 3) shows that the effect of trust leading to acceptance is more substantial for women than men. Hypothesis EDU x ATT → ACC is accepted at a low significance of 0.10. With education moderators in the model, the effect between attitude and acceptance weakens (refer to Fig. 4). The remaining hypotheses are rejected.

5. Discussion

The study's results indicate that trust directly impacts the acceptance of OSAs in e-commerce. This finding aligns with past research that shows that higher trust leads to more acceptance of voice-based digital assistants [65]. Trust significantly affects customers' acceptance of chatbots in e-commerce [141]. Trust influences consumers' acceptance of AI service robots [142]. Also, trust is the most crucial element for predicting the acceptance intention of chatbots in online retailing [8]. Hence, trust is essential in accepting OSAs, and increasing trust in the technology can significantly increase acceptance. The present study identifies anthropomorphism and usefulness as significant drivers of trust in OSAs. Past studies have empirically validated that anthropomorphism influences customers' trust in chatbots in e-commerce interactions [29]. Researchers have identified usefulness as an essential factor affecting trust in a website for purchase [143]. The results also indicate that consumer attitude towards OSA directly impacts its acceptance. A previous

Table 4
The reliability and convergent validity.

Factor	α	CR	AVE
ACC	0.934	0.936	0.721
ANT	0.923	0.928	0.686
ANX	0.921	0.944	0.679
ATT	0.959	0.96	0.83
EAS	0.83	0.848	0.592
ENJ	0.788	0.792	0.611
PER	0.867	0.913	0.641
PRI	0.857	0.888	0.692
RAP	0.737	0.741	0.654
SNI	0.846	0.858	0.683
SOC	0.839	0.852	0.674
SOP	0.867	0.88	0.655
TRU	0.976	0.976	0.875
USF	0.769	0.837	0.573

Table 5
The discriminant validity: HTMT ratios.

	ACC	ANT	ANX	ATT	EAS	ENJ	PER	PRI	RAP	SNI	SOC	SOP	TRU	USF
ACC														
ANT	0.64													
ANX	0.422	0.303												
ATT	0.771	0.546	0.348											
EAS	0.609	0.525	0.349	0.427										
ENJ	0.552	0.451	0.342	0.388	0.529									
PER	0.075	0.077	0.092	0.106	0.143	0.079								
PRI	0.177	0.321	0.174	0.154	0.272	0.575	0.196							
RAP	0.284	0.324	0.166	0.239	0.233	0.257	0.119	0.158						
SNI	0.588	0.492	0.475	0.497	0.486	0.759	0.116	0.424	0.211					
SOC	0.291	0.133	0.129	0.293	0.29	0.173	0.136	0.059	0.108	0.16				
SOP	0.523	0.41	0.346	0.395	0.53	0.602	0.098	0.477	0.27	0.679	0.091			
TRU	0.63	0.587	0.266	0.566	0.38	0.403	0.133	0.243	0.224	0.378	0.185	0.328		
USF	0.608	0.501	0.224	0.454	0.517	0.522	0.096	0.244	0.282	0.497	0.145	0.539	0.448	

study showed that attitude directly affects the intention to use smartphone chatbots for mobile shopping [1]. A positive consumer attitude towards chatbot acceptance in services is vital for chatbot acceptance [144].

The study's results support the TAM [30] constructs, usefulness, and ease of use as essential predictors of attitude towards and acceptance of OSAs. A similar study reveals that usefulness and ease of use have a significant role in developing a positive attitude towards voice assistants in e-commerce [145]. Consumers' attitude towards innovative technologies in shopping is determined by usefulness and ease of use, while acceptance of these technologies is determined by usefulness [146]. Also, usefulness and ease of use significantly impact attitudes towards smartphone chatbots in mobile shopping [1]. Previous studies have also adopted the TAM and found that usefulness and ease of use are essential to developing a positive attitude towards AI devices in fashion e-commerce [41]. Even [31] used the TAM to understand the acceptance of voice assistants and observed that usefulness and ease of use positively affect consumers' attitudes towards these technologies. Moreover, perceived usefulness increases customers' acceptance of AI fashion chatbots as digital shopping assistants [60].

The present study found that users' privacy concerns directly impact their acceptance of OSAs. Conversational digital assistants bring privacy issues regarding gathering, storing, and sharing users' personal information [65]. The personalization-privacy paradox makes it difficult for users to obtain personalized services without compromising privacy [147]. Past research shows that privacy concerns negatively influence the acceptance of digital voice assistants [148], acceptance of chatbots for customer communication in online retailing [11], adoption of chatbots as customer service assistants [48], and consumers' acceptance of chatbots for efficient shopping experiences [2]. Hence, privacy has a crucial role in technology acceptance, and marketers must focus on decreasing the privacy risk in using OSAs.

The study's results indicate that anthropomorphism is an essential determinant of consumers' trust, attitude, and acceptance of OSAs in e-commerce interactions. The findings align with a recent empirical study that found that anthropomorphism has the most critical role in forming a positive attitude and intention to use digital assistants for purchases [52]. Moreover, anthropomorphism positively affects customers' attitudes and adoption of mobile commerce [149], acceptance of mobile messenger chatbots in online shopping [51], and customer attitude towards digital assistants [150]. Past research proves anthropomorphism influences customer trust in AI service robots [75] and chatbots [29]. However, there is also empirical evidence that anthropomorphism hurts trust in chatbots for online shopping [151]. Hence, future researchers can further investigate which anthropomorphic characteristics of OSAs positively and negatively affect customers' trust.

The study also highlights that enjoyment increases OSA acceptance in e-commerce interactions. This result is similar to studies on mobile commerce acceptance [152] and acceptance of chatbot services in online shopping [60]. OSA designers can give the users options to customize the technology interface as per their needs, which will enhance users' experiences, and they will accept it. The study found that sociability affects customers' attitudes and acceptance of OSAs. Sociability facilitates the acceptance of humanoid retail service robots for personalized shopping assistance [49]. Also, social network influence drives attitudes towards OSAs. This finding is consistent with a previous study that found that customers' social network members impact their attitudes [79].

The moderation analysis indicates that consumers' gender and education significantly moderate the effects of trust and attitude on acceptance of OSAs. Empirical evidence exists on the moderating effect of gender on the acceptance of chatbots for mobile shopping [1] and digital assistant acceptance in online purchasing [153]. The moderation analysis indicates that women are more likely to accept trustworthy OSAs than men. Highly educated consumers are more likely to accept OSAs if they trust these technologies, while less educated consumers will accept OSAs if they have a positive attitude towards them. Hence, gender and education are crucial variables for segmenting the users of OSAs.

6. Implications

6.1. Theoretical contribution

The study contributes to the "technology acceptance" literature by extending the original TAM proposed by Davis [30] to accept

Table 6
The correlation matrix.

	ACC	ANT	ANX	ATT	EAS	ENJ	PER	PRI	RAP	SNI	SOC	SOP	TRU	USF
ACC	1.000													
ANT	0.176	1.000												
ANX	−0.420	−0.177	1.000											
ATT	0.626	0.211	−0.349	1.000										
EAS	0.347	0.001	−0.181	0.326	1.000									
ENJ	0.324	0.049	−0.123	0.338	0.029	1.000								
PER	0.402	0.116	−0.293	0.343	0.214	0.572	1.000							
PRI	−0.271	−0.081	0.186	−0.212	−0.061	−0.331	−0.485	1.000						
RAP	0.573	0.170	−0.441	0.527	0.196	0.520	0.505	−0.223	1.000					
SNI	0.081	0.042	0.087	0.146	0.130	−0.093	−0.023	0.131	−0.117	1.000				
SOC	0.435	0.563	−0.342	0.488	0.193	0.453	0.387	−0.227	0.427	−0.078	1.000			
SOP	0.236	0.336	−0.137	0.246	0.118	0.345	0.556	−0.333	0.208	0.129	0.355	1.000		
TRU	0.774	0.205	−0.360	0.443	0.313	0.248	0.344	−0.218	0.491	0.109	0.367	0.187	1.000	
USF	0.634	0.111	−0.298	0.544	0.110	0.395	0.295	−0.291	0.496	0.071	0.415	0.188	0.541	1.000

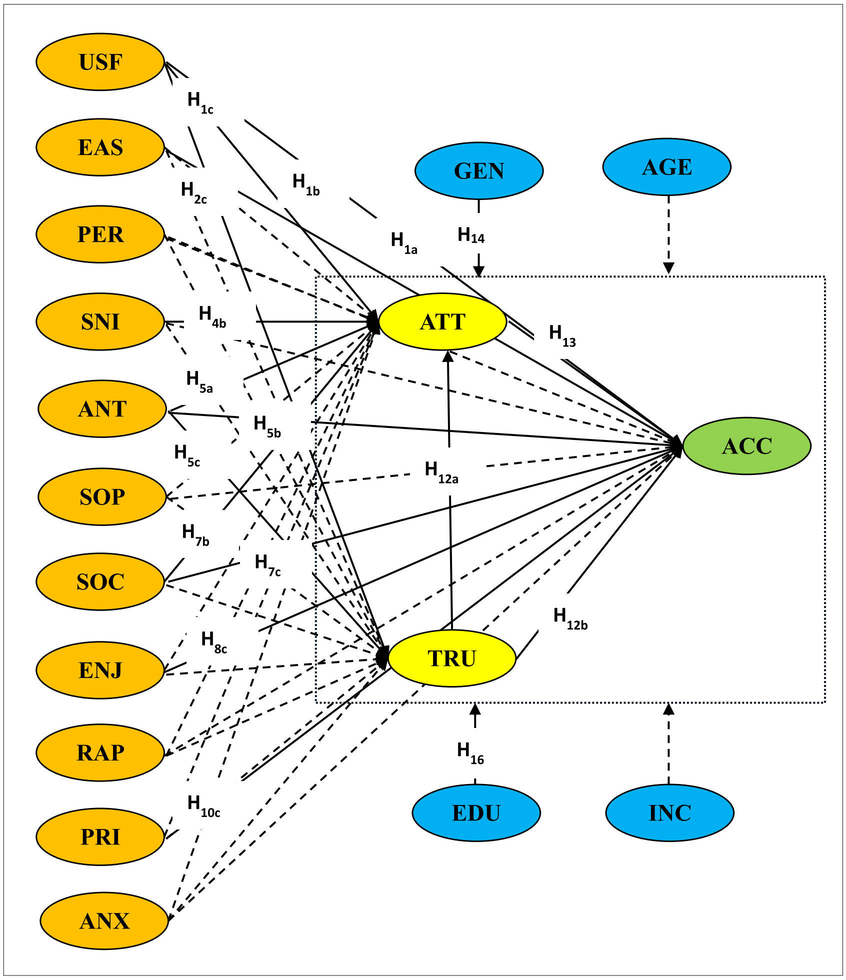

Fig. 1. The PLS-SEM model of OSA acceptance in e-commerce (self-developed using Primary estimates).

OSAs in e-commerce. Significant factors of OSA acceptance are "usefulness," "ease of use," "anthropomorphism," "sociability," "enjoyment," "privacy," and "trust." The research contributes to the "consumer behavior" literature by examining customer motivations to accept OSA in e-commerce interactions. The paper identifies crucial determinants of consumer trust, attitude, and acceptance of OSAs. The study contributes to the existing knowledge on "HCI" factors of consumer acceptance of OSA in e-commerce. Significant HCI factors are anthropomorphism and sociability.

6.2. Practical implications

The study results will guide e-commerce companies in developing strategies to design and implement OSAs to enhance customers' online shopping experience. Managers should pay attention to significant factors for increasing consumer acceptance of OSAs. The impact of anthropomorphism on trust is the most significant effect. Human-like OSAs result in more trust among customers, further increasing acceptance. The most potent effect is the impact of trust on attitude, which points toward the importance of designing a trustworthy OSA technology. The research findings have important implications for policymakers in the growing Indian e-commerce market through online assistant technology. Policymakers must ensure people's data are secure online to increase online commerce and acceptance of such emerging technologies.

7. Conclusion

Given the progress in developing and utilizing OSAs in e-commerce interactions, a comprehensive study of the acceptance of this contemporary technology is needed. This study proposes and empirically validates the proposed model of OSA acceptance. The results show that acceptance is impacted significantly and positively by anthropomorphism, attitude, ease of use, enjoyment, sociability, trust, and usefulness but negatively by privacy risk. Attitude is impacted substantially and positively by anthropomorphism, social network influence, sociability, trust, and usefulness. Trust is impacted significantly and positively by anthropomorphism and usefulness. There

Table 7
The PLS-SEM path estimates.

Hypothesis	Path Coefficients	T statistic	P values	Decision
ANT → ACC	**0.127**	**2.886**	**0.004**	**Supported**
ANT → ATT	**0.182**	**3.133**	**0.002**	**Supported**
ANT → TRU	**0.401**	**5.557**	**0.000**	**Supported**
ANX → ACC	−0.061	1.443	0.149	
ANX → ATT	−0.092	1.635	0.102	
ANX → TRU	−0.084	1.438	0.150	
ATT → ACC	**0.369**	**7.581**	**0.000**	**Supported**
EAS → ACC	**0.137**	**3.236**	**0.001**	**Supported**
EAS → ATT	0.012	0.194	0.846	
EAS → TRU	−0.013	0.145	0.885	
ENJ → ACC	**0.105**	**2.132**	**0.033**	**Supported**
ENJ → ATT	−0.046	0.741	0.459	
ENJ → TRU	0.075	0.969	0.333	
PER → ACC	−0.037	0.984	0.325	
PER → ATT	0.029	0.635	0.525	
PER → TRU	0.119	1.854	0.064	
PRI → ACC	**−0.133**	**2.964**	**0.003**	**Supported**
PRI → ATT	−0.071	1.183	0.237	
PRI → TRU	0.061	1.005	0.315	
RAP → ACC	0.003	0.076	0.940	
RAP → ATT	−0.019	0.415	0.678	
RAP → TRU	−0.027	0.520	0.603	
SNI → ACC	0.010	0.195	0.845	
SNI → ATT	**0.172**	**2.394**	**0.017**	**Supported**
SNI → TRU	0.009	0.127	0.899	
SOC → ACC	**0.088**	**2.303**	**0.021**	**Supported**
SOC → ATT	**0.168**	**3.756**	**0.000**	**Supported**
SOC → TRU	0.053	0.883	0.377	
SOP → ACC	0.080	1.618	0.106	
SOP → ATT	0.052	0.776	0.438	
SOP → TRU	−0.008	0.101	0.919	
TRU → ACC	**0.179**	**3.992**	**0.000**	**Supported**
TRU → ATT	**0.294**	**5.343**	**0.000**	**Supported**
USF → ACC	**0.122**	**2.681**	**0.007**	**Supported**
USF → ATT	**0.119**	**2.269**	**0.023**	**Supported**
USF → TRU	**0.166**	**2.762**	**0.006**	**Supported**

Table 8
The PLS-SEM path estimates for moderation analysis.

Hypothesis	Path Coefficients	T statistics	P values	Decision
EDU x TRU → ACC	0.623	15.027	0.005	Supported
INC x TRU → ACC	0.074	0.082	0.647	
AGE x ATT → ACC	−0.018	0.005	0.394	
AGE x TRU → ACC	0.155	0.022	0.402	
INC x ATT → ACC	−0.014	0.008	0.556	
EDU x ATT → ACC	**0.077**	**0.023**	**0.075**	**Supported**
GEN x ATT → ACC	−0.127	0.012	0.212	
GEN x TRU → ACC	**0.120**	**0.026**	**0.064**	**Supported**

is a significant moderating effect of gender and education qualification on acceptance of OSAs.

The research has some limitations that provide good opportunities for upcoming examinations. First, the hypotheses were tested using self-reported data from the survey participants. We had put considerable effort into screening the participants and inciting them to respond as objectively as possible. Still, there might be biases in the responses, as we could not confirm that the participants had ever used an OSA as they claimed. Thus, future research could have an experimental design where participants are invited to use a particular OSA before evaluating their experiences. Second, the study is on accepting OSAs in low-risk consumer products. Future studies can investigate the acceptance of high-risk technologies (e.g., self-driven vehicles) to assess the role of trust and other vital determinants in adopting these technologies. Third, future research can examine how cultural factors play a role in accepting e-commerce OSAs and building attitudes toward them. Fourth, to extend the present study, future researchers can apply Multi-criteria decision-making (MCDM) techniques to analyze the cause-and-effect relationships among the factors of OSA acceptance.

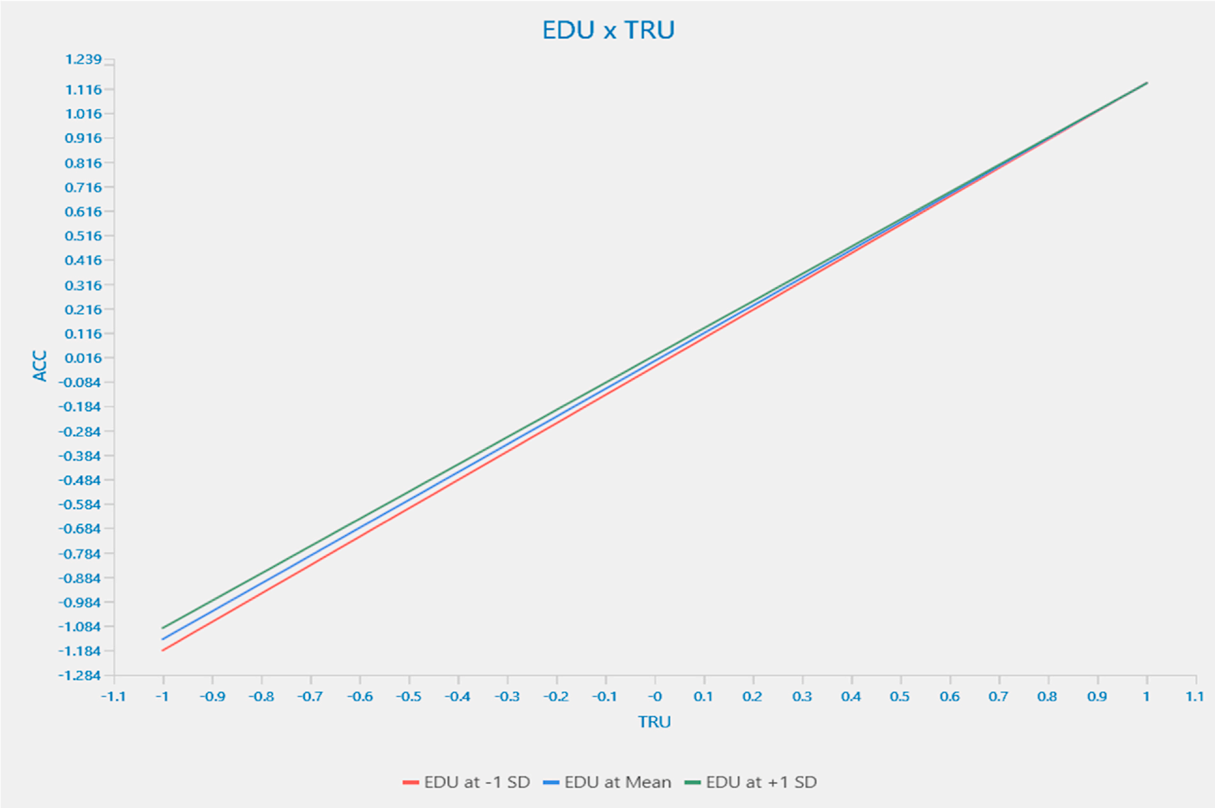

Fig. 2. The simple slope of the EDU moderator impact on TRU → ACC (Source: SmartPLS 4).

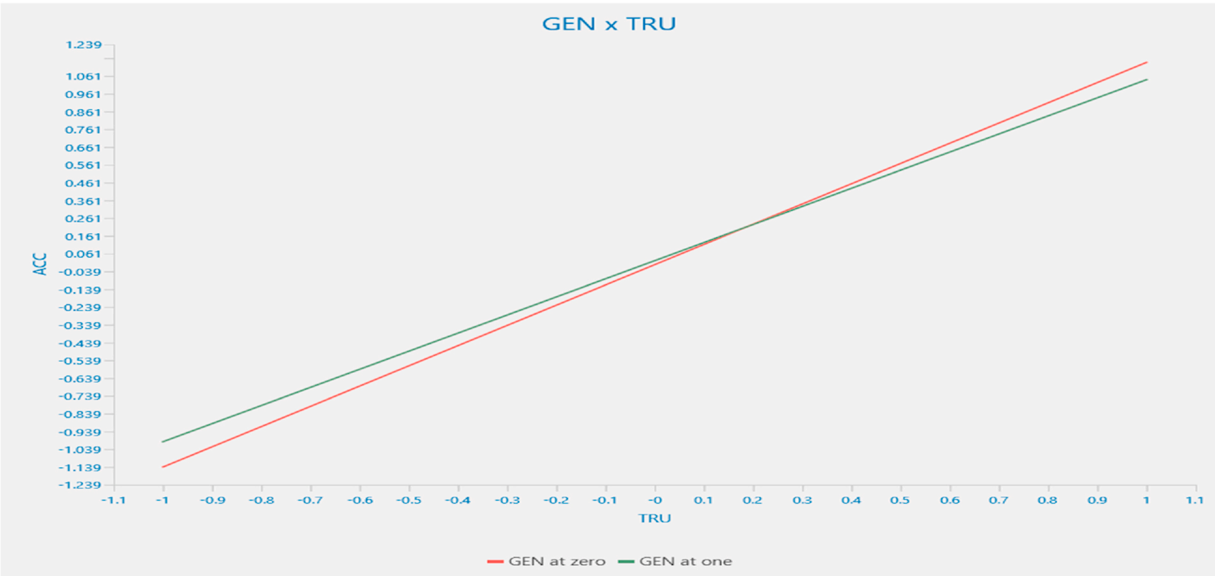

Fig. 3. The simple slope of the GEN moderator impact on TRU → ACC (Source: SmartPLS 4).

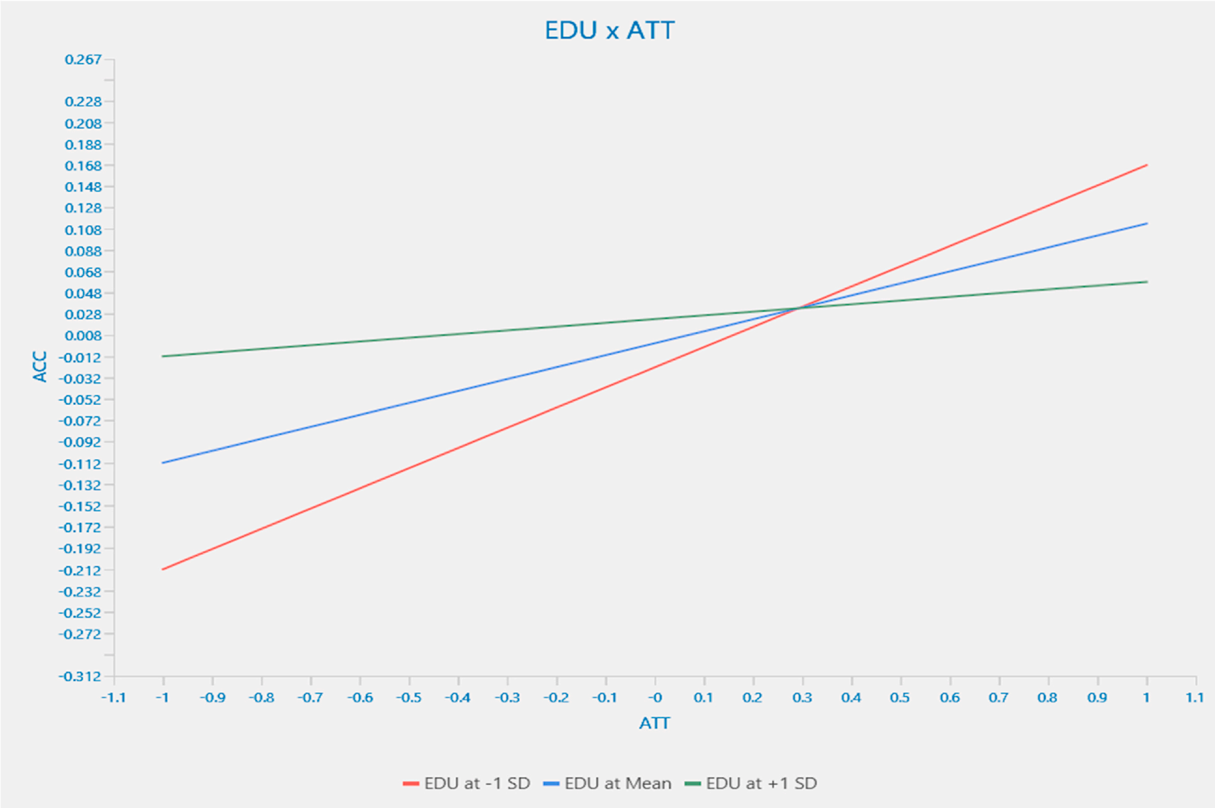

Fig. 4. The simple slope of the EDU moderator impact on ATT → ACC (Source: SmartPLS 4).

Consent statement

All questionnaire respondents were informed that their data would be stored anonymously and used for the study's research.

Data availability statement

The data is not available publicly. Data will be made available on request.

CRediT authorship contribution statement

Chetanya Singh: Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Manoj Kumar Dash:** Writing – review & editing, Validation, Supervision, Methodology. **Rajendra Sahu:** Writing – review & editing, Project administration, Data curation, Conceptualization. **Anil Kumar:** Writing – review & editing, Supervision, Project administration, Data curation.

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. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2024.e25031.

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