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Consumer Perception of Conversational Commerce from the Perspective of Bangladesh

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&
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Abstract: *The use of Conversational Commerce tools (AI-powered chatbots, messaging apps, voice assistants, and live chats) is getting popular gradually across the world to attract more customers online. The study focuses on studying the appliances of conversational commerce and their underlying impact on consumers' perception of accepting and adopting conversational commerce from the perspective of Bangladesh. The study used the Technology Acceptance Model (TAM) 3 to determine the variables that influence consumers' perceptions. A questionnaire was formed based on the 14 variables of TAM and distributed to gather data from 106 Bangladeshi web users using a multistage sampling method. The study analyzed the collected data based on the Confirmatory Factor Analysis (CFA) model using AMOS and SPSS V29. The paper outlines that the adoption and acceptance of conversational commerce mainly depend on consumers' behavioral perceptions. And the behavioral intention that influences consumers buying decisions is significantly impacted by the perceived usefulness of conversational commerce. Furthermore, the perceived effectiveness of conversational commerce is affected mainly by consumers' perceived ease of use. Moreover, the article highlights promising growth in the acceptance of C-commerce as around 85.5% of the respondents preferred to interact with brands by using messaging applications. The paper also identified customer service as the most vital point of satisfaction, yet the emerging realm of conversational commerce is replete with difficulties that manifest mainly in the form of discontentment of Bangladeshi consumers through lack of consultation and additional trouble during purchases.*

Keywords: Conversational Commerce, Conversational Ecosystem, TAM 3, Consumer Perception, VUIs, SDSs, ECAs, Chatbot, Confirmatory Factor Analysis, Perceived Each of Use, Behavioral Intention

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1. Introduction

1.1 Background of the Study

With the rise of online-based communication and web users, e-commerce has changed. Brands are trying to keep up with consumer expectations, making good brand-customer contact important to creating ongoing consumer engagement (Donna and Novak, 1997). Chris Messina's conversational commerce allows companies and customers to connect electronically. Conversational commerce is now possible via messaging interfaces, web-based contacts, and voice input systems in Artificial Intelligence (AI) driven assistants like Google Help and Amazon Echo. This has changed buyer-seller interaction by merging interactive communication and buying into one medium (Exalto et al., 2018; Euwen, 2017; Kröger and Johansson, 2019).

Table 1 Global Conversational Commerce Market by Region

Conversational Interface	Top User Concentrations	2020	2021	2022	2023	2024	2025 (Projected)
Chatbots	United States, India, Germany, United Kingdom, Brazil	\$5.13	\$6.33	\$7.81	\$9.63	\$11.88	\$14.65
OTT Service	North America, Latin America, Europe, China and East, Asia	\$42.72	\$45.93	\$48.77	\$51.66	\$51.56	\$51.15
Voice Assistant	North America, Europe, Asia Pan Pacific, South America, Middle East	\$2.48	\$2.80	\$3.34	\$4.38	\$5.72	\$7.30

Source: A2P SMS revenues by region 2025, Statista, Taylor (2023)

The empirical studies of authors like Mehta et al. (2022) and Schanke et al. (2021) showed that, by 2025, the multibillion-dollar global speech recognition market is expected to get on a boom that will help chatbots to propagate. While there are already over 9 billion worth of chatbots in the market as opposed to just 2.5 million in 2018, the chatbots are estimated to carry out 85% and 85% of the customer service interaction for banking and healthcare institutions respectively by 2022 (Table 1). Those regions with a lot of internet-users like the United States and India rank higher for marketing issues through chatbots to address. This growth is due to the internet's omnipresence with 92% mobile users summing up over 4.66 billion users globally and the great user base of social media networks like Meta’s Messenger and Instagram exceeding 1.2 billion users (Figure 1) showing the evidence to the wide adoption of chatbots on virtual assistants (De Cosmo et al., 2021). Broadly, the internet's overwhelming influence, smartphones' superiority, and speech recognition's progression are nurturing the future milieu dominated by chatbots, which consequently will turn the customer service into an intelligent and automated atmosphere.

Conversational commerce has numerous benefits over conventional e-commerce since it offers users a variety of tailored services with real-time interactive communication (Kröger and Johansson, 2019). Facebook and WhatsApp developed chatbots in 2016 as conversational commerce advanced. The world's chat commerce industry is booming, with estimates of it reaching the $11 billion mark by 2024. Chatbots alone are estimated to have 1.4 billion active users worldwide with top user densities in mostly the US, India, Germany, UK and Brazil (Table 1). OTT services like WhatsApp have 2 billion monthly users, according to Statista (2021). Due to the absence of conversational interfaces, countries like Bangladesh are still in the infancy stage, but local businesses like MCC Limited, REVE systems, and PreneurLab are creating both conventional and conversational AI-based bots (Halim, 2019). Shwapno, Chaldal, and Aarong use conversational chatbots with live chat systems to meet evolving client needs in Bangladesh's retail industry. Conversational commerce, its effects on customers, and how it changes e-commerce are covered in this research. Conversational commerce may blend interactive communication and buy into a single medium, making it more user-friendly and offering customers a variety of tailored options, according to the research.

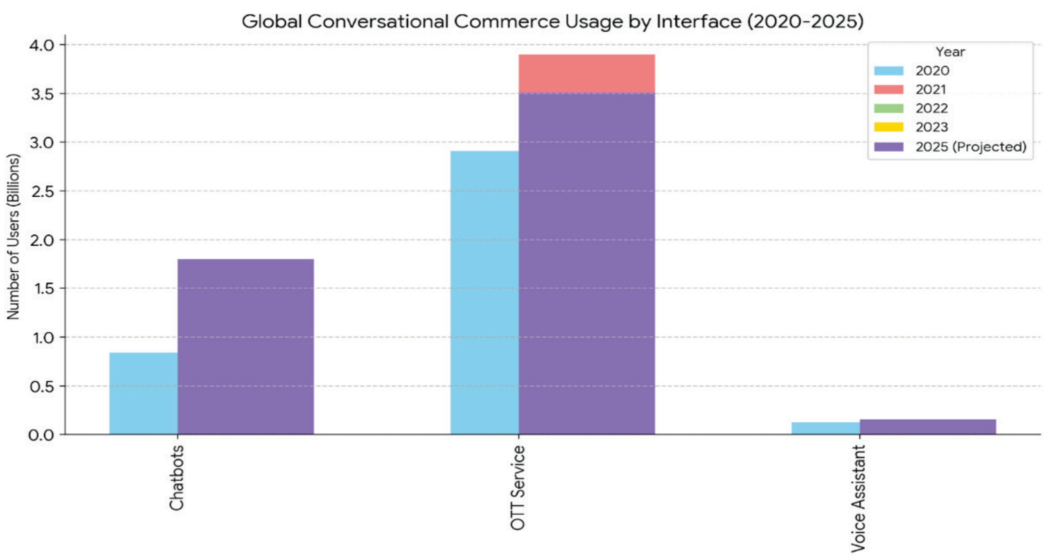

Figure 1: Global Conversational Commerce Usage (Mehta et al., 2022)

1.2 Statement of Problem

The ongoing growth of demand leads to the growth of online shopping systems or e-commerce in the system. The development of electronic media and the revolution of "Information Communication and Technology (ICT)" has provided the opportunity to connect from one end to the other end of the country. As the whole country's people have become tuned up to the increasing internet usage, availing online goods and services has become one of the key aspects for business. However, the ongoing growth of online consumers has also increased the need for immediate customer service. Although online shopping created an intense opportunity for consumers and companies, businesses are still facing a hard time coping with the intensified demands of consumer service. However, in the last era, some businesses started using conversational chatbots, which alleviated the problem to some extent. People tend to use social platforms like Messenger rather than other mediums like WhatsApp, Telegram, Discord etc. Few tech-oriented companies like Banglalink started to use features like "messenger bot," which

helped consumers get real-time customer service, resulting in a seamless consumer experience. However, as the idea of virtual interaction with the business is relatively novel, many consumers are showing reluctance to this type of system. Besides, consumer perception acts as a critical component in the adoption of any new ideas or systems. So, the article is based on consumer perception of chat and voice commerce usage in Bangladesh. The study will focus on the consumer behavioral aspect, perception, and their effects on the purchase decision.

1.3 Research Questions

The above-described problem statement identified that the subject is explored to point out the potential solution to three core questions. The questions are accurately stated as:

RQ1: Is voice commerce essential or counted as an optional element in the perspective of business?

RQ2: How does the use of chat and voice commerce increase business growth?

RQ3: How does conversational commerce influence user satisfaction?

1.4 Objectives of the Research

The objective of the paper portrays the synopsis of the concept of conversational marketing in the Bangladeshi context. Both the appliances and the impacts of conversational commerce have been covered in the paper. The paper focuses mainly on the consumer behavioral perspective regarding C-commerce. Specific objectives that will be covered in the article are shown below:

A. To identify the user perception regarding conversational commerce.
B. To explore the applications of conversational commerce that are applied from the perspective of the Bangladeshi market.
C. To find out the practical issues of conversational commerce that can assist businesses in Bangladesh.

2. Literature Review

As the subject matter Conversational Commerce is entirely novel, only a few pieces of research have been covered on the topic that specially focused on consumer perception. Although the concept of commerce includes various trends, including the use of chatbots, highly configured notifications, the appliance of knowledge bots, many of the researches mainly focuses on the appliance and impacts of chatbots from both the perspective of business and consumers (Tuzovic and Paluch, 2018; Hristidis, 2018; Syam and Sharma, 2018; Buhalis and Cheng, 2020; McTear, 2017). However, few researchers (Perez-Vega et al., 2020; Castillo et al.,2021; Gnewuch et al., 2020) have analyzed conversational commerce's perceived dominance. However, both the appliance and perceived value of conversational commerce is yet to be analyzed in the Bangladeshi market. This paper investigates conversational marketing platform client preferences. Perez-Vega et al. (2020) outlined that chat commerce had drastically changed the consumer experience (CX) by initiating messaging platforms for providing customer convenience. Conversational chatbots also revolutionized the directions of shopping by providing automated decision support. Huang and Rust (2018) showed that as the AI interfaces started to evaluate empathetic tasks, C-commerce began to measure consumers' emotional aspects and provide customization and recommendation service based on those aspects. Leung et al. (2018) found that consumers tend to avoid automated recommendations. However, logg et al. (2019) argued that sometimes algorithmic suggestions are accepted in the customer base if the recommendations are backed up by the previous user experience of the customer. Brand experts prefer chat commerce because its interfaces offer highly automated narratives backed up by rich interactive algorithms beyond humanoid interactions (Saad, 2016). Kumar et al. (2016) remarked that chat commerce makes certain service firms "information-rich." Big data lets organizations improve operations with automated conversational AI (Ukpabi, 2019).

eMarketer (2017) argued that 70% of millennials born from the late 90s to the early 2000's of tend to accept conversational marketing more than baby boomers who fall in the age group of 56-74 years old. Saffarizadeh et al. (2017) claimed that the caution of privacy breach often led individuals to disclose private data as they do not trust any human-substitutions like AI interfaces. Conversational commerce's personalized support has helped companies deliver good customer service. (Sotolongo and Copulsky, 2018). Gnewuch et al. (2020) found that conversational interfaces encourage consumers to consult commercial interfaces for future purchases. Buhalis and Cheng (2020) found that consumers prefer "Transactional" chatbots, which are pre-programmed to handle delivery and transaction inquiries. MCC and Rave Systems have constructed commercial chatbots for 11 Bangladeshi companies, providing character-oriented customer service that has increased profits by 20-40% (Halim, 2019).

2.1 Concept of C-commerce

As the concept of chat commerce, also known as C-commerce, is quite novel, there is no fully-fledged definition for this term. However, distinct researchers like Messina (2015), Eeuwen (2017), and Exalto et al. (2018) came up with specific definitions based on their perceptions. As the viewpoint varies from researcher to researcher, the definition varies in terms of text or chat commerce vs voice commerce. Besides, researchers also argued on the concept of whether C-commerce depends on Chatbots or solely on human interactions (Kröger and Johansson, 2019). The term conversational commerce was first coined by Chris Messina in a blog on the proposed topic published in "Medium." According to Messina (2016), "*Conversational commerce is the process of using messaging, chat, or other AI interfaces to communicate with people, companies or brands and bots that takes place in the bidirectional and asynchronous natured texting."* Researcher Eeuwen (2017) defined conversational commerce as a process that offers convenience to users by enabling them to interact in natural language (NL). Besides, the founder of Chatbot magazine, Matt Schlicht, defined conversational commerce as: "*An automated technology backed up by scripted programs and AI that helps create a connection between brands and online users by interacting via chat or voice assistants*" (Schlicht, 2018). Furthermore, Exalto et al. (2018) defined conversational commerce as: "the *exchange of questions and answers in a mode that the customer determines and to clarify uncertainties of the potential customer to support him/her during the customer journey."* Although most of the definitions varied in some sense, each definition outlined conversational commerce as a medium of virtual interaction between brands and users.

2.2 Conversational Ecosystem

The usage of automated tools and apps has led to the development of human-technology interaction. Voice user interfaces, Spoken dialogue systems, Embodied conversational agents, and Chatbots are all depending on one another in the development of conversational interfaces, as explained by Dix (2016). Voice user interfaces, often known as virtual voice assistants, are conversational and automated setups that begin dialogue based on speech and chat-based data. Gardner (2017) explains that, like chatbots, speech interfaces may take into account the user's choices and act appropriately.

According to Pan (2017), embodied conversational agents are computer-generated animated characters that provide consumers with a humanlike experience by emulating human facial emotions, body language, symbolic gestures, and speech. The two main types of natural language interfaces for conversational agents are those that emphasize the usage of the user's voice and those that emphasize text-based conversing. (McTear, 2017). Conversational Bots, the next generation of chatbots, are scripted for operation on the cloud and can mimic human speech in real time. (Chung et al., 2017). Even while chatbots' language interfaces used to be complicated by factors like background noise and foreign accents, modern technology has made it so that they can engage with customers more naturally. (Baier et al., 2018). Essentially, the evolution of conversational interfaces and chatbots has made user interfaces more engaging and intuitive. These innovations are poised to make significant contributions across a range of sectors. As shown by Google's Alpha G, conversational skill has increased by the constant usage of AI and cognitive technologies including voice recognition, machine learning, and natural language processing. (McTear et al., 2016; Song et al., 2019).

2.3 Simplification of the Conversational Commerce Process

The term "conversational commerce" refers to an emerging business practice that entails two levels of process: the customer's or client's journey and their activities; and the company's or organization's conversation function, strategy, capabilities, and institutional enablers. (Tuzovic and Paluch, 2018). According to Eeuwen (2017), organizations need to know their customers well before deciding whether to use a transactional chatbot, voice agent or omnichannel employing AI-oriented channels. According to Hamilton and Price (2019), there are five stages of the customer journey: awareness, deliberation, preference, retention, and use (Figure 2). On the other hand, consumer activity is the consumer behavioral process that includes three distinct stages: pre-purchase, purchase, and post-purchase (Ramkumar and Ellie, 2019). The awareness stage of the consumer journey refers to the identification of the problem. In this stage, consumers search for the solution to the practical problem and discover the proper solution. The consideration stage leads the consumer to conduct a preliminary search for a solution. A single pre-purchase process now connects both stages due to conversational commerce. The “conversational discovery” by using AI interfaces leads consumers to get various providers who can solve their problems. The preference stage refers to the stage when consumers prefer to make the right purchase decision. Business needs to make sure consumers are making the right decision in the right mind. So, “conversational shopping” helps consumers provide an array of customized recommendations with interactive communication via conversational interfaces, leading them to make suitable decisions. The last two stages suggest the post-purchase stages of the consumption life-cycle. The retention stage suggests the brand loyalty that consumers show when users connect with brands. Furthermore, the usage stage also shows brand loyalty, but it occurs when consumers become brand ambassadors. The “interactive communication” offered by C-commerce helps businesses become user-friendly, which helps create long-lasting business relationships.

Conversational commerce bridges the gap between these two phases by facilitating appropriate customer decision-making through personalized suggestions delivered via conversational interfaces. Businesses require careful planning, the identification of a suitable touchpoint, an adequate evaluation of their customer base and the reasons for user engagement, and the selection of an appropriate conversational strategy to ensure its effective implementation. (Tuzovic and Paluch, 2018). Both the "channel approach" and the "user experience approach" are examples of this method being employed by firms for communication rather than sales at present. (Tuzovic and Paluch, 2018). Conversational commerce only really works for low-involvement orders, and sophisticated activities still need human support. (Tuzovic and Paluch, 2018). C-commerce provides companies with fresh chances to forge meaningful connections with clients. However, before introducing technical innovation, it is essential to choose the best conversational strategy. (Tuzovic and Paluch, 2018; Eeuwen, 2017; Hamilton and Price, 2019; Ramkumar and Ellie, 2019).

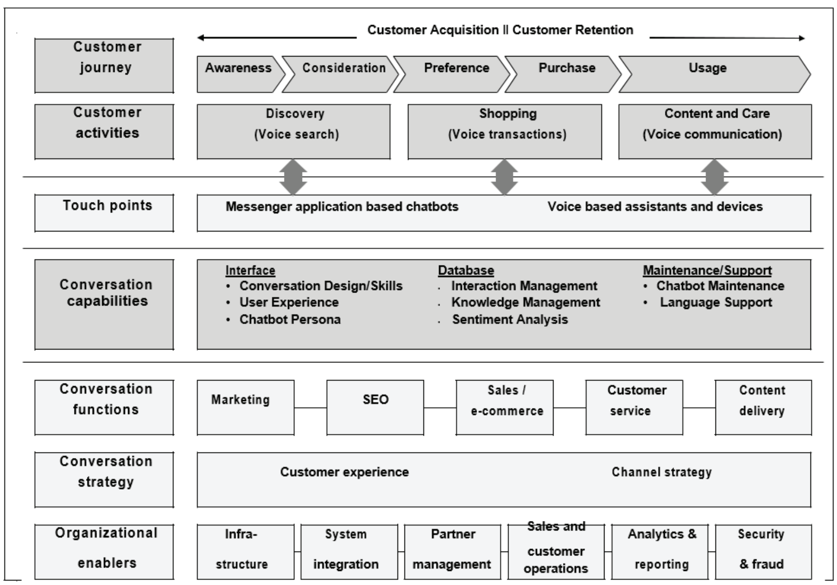

Figure 2: Five Stages of Consumer Journey (Hamilton and Price, 2019)

2.4 Perception and Attitude towards Conversational Commerce

The components of conversational commerce are affected by consumer viewpoints and attitudes. Ajzen and Fishbein (1980) describe attitude as the customer's ideas and feelings regarding a specific setting, however, Hestschel (1986) says consumer perception is a process that includes emotional conditions and earlier experiences. Customers' mental images and perceptions influence whether they will try a new product or service, according to Sjoberg (1999).

Businesses may add value to consumers' perspectives and preferences by supporting one-on-one interactions and a two-way flow of information, according to Schlicht (2018). Conversational commerce's live chat boosts consumer loyalty, according to Qui and Benbasat (2005). Eeuwen (2007) found that chatbots have a positive connection over consumer's beliefs and the practical usefulness of chatbots. Besides, the author has also drawn positive relation over the user-friendliness and the user's perception towards the messaging assistants. Also, there is a positive relationship between consumer adaptiveness and user preference over chatbots. As pointed out by Mimoun and Poncin (2015), the attributes of e-commerce are control, access, and adjustability, which soothes the shopping experience of consumers. Although e-commerce provides the opportunity to shop remotely, the medium does not provide the "real-time" interactive communication that consumers prefer while shopping. However, c-commerce provides the opportunity for virtual interactive communication along with other attributes of e-commerce. According to Wren (2021), around 83% of consumers worldwide interact with brands by using conversational assistants, and around 75% of those consumers transact after the pre-purchase interaction. Conversational commerce allows consumers to switch from channel to channel seamlessly, which helps to provide a consistent omnichannel experience.

2.5 Research Gap

Only limited studies are found on the concept of the consumers' perception of conversational commerce adoption. Most of the earlier studies focused on the appliance and impacts of AI assistance from a business perspective. Besides, most of the data on the concept of the willingness to adopt and use chat-commerce has mainly come from studies that focused primarily on the European and US markets (Kröger and Johansson, 2019). Furthermore, the evidence for the Bangladeshi market is quite rare as the concept of conversational commerce is relatively unknown in most of the consumer market. The study also encountered a knowledge gap as the article could not identify the Bangladeshi consumers' perception of the omnichannel that suppliers use to strengthen the C-commerce experience because of the logical inconsistencies in multiple empirical studies.

2.6 Contribution of the Study

The research performed an introductory or preliminary analysis based on Technology Acceptance Model (TAM) 3 which evaluates the adoption rate of a novel technology by assessing a person's behavioral intention, a new addition to the empirical study of conversational commerce, guiding further research. Besides, the study also collected a new dataset on the concept of conversational commerce, providing references for future research purposes. Moreover, the local businesses are both tech startups and retail chains like Meena Bazar, Swapno, Arong etc. will be helpful as the study provided a proper understanding of consumer behavior and acted accordingly. Furthermore, the study shows a brief understanding of consumer preference, perception, and loyalty toward conversational assistance.

3. Methodology

3.1 Research Philosophy and Approach

The study used a two-stage research technique, with the first stage consisting of exploratory qualitative research and the second stage being a quantitative examination of customer impression using an extensive questionnaire. The use of a structured questionnaire and an emphasis on quantitative data suggest that positivism, with some pragmatic overtones, was the guiding study ideology. Accurate information was gathered using a combination of primary and secondary data sources such as books, papers, and case studies (Tuzovic and Paluch, 2018; Saunders et al., 2009; Morgan, 2014).

3.2 Survey Design

To gain insights into online shopping habits, a two-phase study was conducted with 110 volunteers. In the initial phase, face-to-face conversations occurred to gather demographic data and to get a preliminary understanding of the participants' online shopping behaviors (Myers et al., 2011). Following this, those willing to participate further were sent a detailed questionnaire via email to ensure a comprehensive data collection process, capturing both broad trends and specific details through in-person interaction and a structured survey.

The study questions were answered with the use of a Google form questionnaire designed using the TAM. In the first phase, the survey gathered demographic information, and in the second, it employed 13 different versions of the TAM 3 framework. Adapted from Sullivan and Artino (1992), the 5-point Likert scale was used to evaluate responses to questions based on Venkatesh and Davis (2000). Descriptive statistics were utilized to examine the demographic data obtained between June 24 and June 30, 2021, and the Likert scale was employed to gauge participants' agreement with the TAM questions.

3.3 Sampling

Primary data about the consumers' tendency to accept conversational marketing has been collected from the volunteered 110 respondents who are accustomed to virtual shopping by using online questionnaires, The questionnaire was also posted throughout the online social media platforms. Stratified sampling method was used to select subgroups that represent target groups with focus on the major demographic characteristics as age, gender, income level or education are created in a manner which covers needs of online shoppers across segments depending on their economic and social status. Sedgwick (2015) claimed that this homogeneity of data reduces bias and provides leaner insight into online consumer behavior. An online questionnaire form was sent through email to the target groups. According to Al-Saleh et al. (2002), multistage sampling or two-stage sampling is a sampling method where the primary sample is selected first. Table 1 details the respondent demographics. A total of 106 people filled out the survey, with an approximate 2% non-response rate resulting in the total sample, n = 106. Jacobucci et al. (2016) showed that samples under 50 are sufficient for fitting a standardized confirmatory factor analysis (CFA) model, which is believed to be conceptually less complicated and more dependable (Field, 2005). As per Myers et al. (2011) the sample size of 106 respondents appears to be adequate as the response rate represents the frequency of responses in similar empirical studies for consumer perception about technology research.

3.4 Data Collection Process

Quantitative analysis, particularly the survey approach, was used to evaluate the link between consumer acceptability of conversational commerce and consumer behavior. Multistage sampling was used to randomly choose respondents from throughout Bangladesh. Before adopting exploratory research techniques, descriptive statistics were used to summarize data. The research employed descriptive-analytical methods such as numerical tools to measure frequencies and relative frequencies of variables to analyze their relationship. (Kaur et al., 2018). SPSS was used for descriptive analysis to characterize subjects. Predictive modeling technologies also assessed the data. A confirmatory factor analysis (CFA) model was also created using AMOS 26, an SPSS V29, to show the link between observable and latent variables.

3.5 Theoretical Framework

The Technology Acceptance Model (TAM3) was used to examine how helpful and simple consumers found conversational commerce. Users' views on individual variation, social persuasion, and enabling words were gathered via a structured questionnaire. Previous research on knowledge management and customer loyalty informed the selection of a confirmatory factor analysis (CFA) model with which to examine the hypotheses.

(Venkatesh and Bala, 2008; Nikolopoulos et al., 2018; Jaradat et al., 2014; Siregar et al., 2017; Lee et al., 2019). Due to the high number of latent and observed factors in the research, CFA analysis was judged appropriate for conducting validity and reliability tests on latent variables and gauging consumers' attitudes toward conversational commerce.

3.5.1 Comparison of Methods

The Theory of Reasoned Action (TRA), the Theory of Planned Behaviour (TPB), and the Technology Acceptance Model (TAM) are just a few of the well-known theoretical models that have been used to investigate the diffusion and use of various technologies (Davis, 1989; Ajzen and Kahneman, 1991; Ajzen and Fishbein, 1980). In comparison to TPB and TRA, TAM is favored for its ability to provide light on the critical aspects influencing user acceptability and adoption. Perceived usefulness (PU), purpose to use, and prior experience are all included in the TAM framework in TAM 2 (Venkatesh and Davis, 2000). TAM 2's primary focus on PU and user intent means it has certain restrictions.

According to Davis (1989), the comparison between TRA and TAM results in the intersection of the TAM and TRA model. In the TPB model, researchers like Yi et al. (2006) argued that social and human factors significantly influence the acceptance of novel technology. However, Shih and Fang (2004) outlined that the TPB model’s subjective norm will not considerably influence behavioral intention (BI) if used in a voluntary setting. Therefore, as the research setting is voluntary, the TPB model will not suit the study. Besides, as the TAM framework is more suitable to address user acceptance and adoption factors, researchers like Chau and Hu (2002) and Lai and Zainal (2015) highlighted that the TAM framework is more favorable than TPB and TRA.

To remedy these shortfalls, TAM 3 was developed to include not just perceived usefulness (PU) but also perceived ease of use (PEoU) determinants and modifiers including user experience and voluntariness. (Venkatesh and Bala, 2008). With its adaptability and multi-level assessment capabilities, TAM 3 is the best fit for our study of the adoption of conversational commerce in the Bangladeshi market. While the Unified Theory of Acceptance and Use of Technology (UTAUT) also considers human and social aspects, it does so exclusively at the organizational level and was thus left out of this study (Dwivedi et al., 2019). Since the TAM 3 model incorporates PU and PEoU factors, as well as user experience and voluntariness, it is chosen to evaluate the rate of adoption of conversational commerce in the Bangladeshi market.

4. Analysis and Findings

4.1 Descriptive Analysis

The description of respondents' personal information such as age, gender, occupation, and so on is provided in the section. Around 110 questionnaires were provided among various parts of Bangladesh, and around 108 responses were returned. After closely examining the validity of responses and removing the irrational responses, around 106 responses were selected as valid data. According to the survey data (Table 2), around 98.1% of the participants use smart devices. Besides, the descriptive statistics show that 63.2% of the respondents heard about conversational commerce, but 36.8% of respondents are not accustomed to the term conversational commerce. Around 74.5% are male participants. As most participants are students (87.7%), the number of millennials (20-30 years old) participants was 89.6%, which is comparatively more significant than other age group participants. Furthermore, the demographic statistics showed that around 91.5 % of respondents prefer Facebook to communicate with brands rather than any other social platform. The rest of the descriptive information of the participants is illustrated in Table (2).

Table 2 Demographic statistics of participants

Variables		*Percentage*	*Frequency*
Gender	Male	74.5	79
	Female	25.5	27
Age	20-30	89.6	95
	30-40	5.7	6
	40-50	1.9	2
	50-60	2.8	3
Use Devices	Yes	98.1	104
	No	1.9	2
Heard CC	Yes	63..2	67
	No	36.8	39
Media Type	Facebook	91.5	97
	Email	1.9	2
	Webpage-based contact	2.8	3
	WhatsApp	2.8	3
	Twitter	.9	1

Source: Primary Data Collection by the researchers

4.2 Hypothesis Formulation

The study is created to identify the relationship between consumer behavioral intention and the rate of acceptance and adoption of conversational commerce. As the TAM 3 model has assessed the tendency of acceptance and adoption, the following hypotheses have been formulated based on the previously mentioned objectives and research questions (RQ).

- **H1:** Perceived usefulness (PU) is expected to be influenced by perceived ease of Use (PEoU).
- **H2:** Behavioral Intention is supposed to be influenced by Perceived Usefulness.
- **H3:** Behavioral Intention is expected to exert influence on Use Behaviour.
- **H4:** Use Behaviour is significantly influenced by Perceived ease of use.
- **H5:** Perceived Enjoyment is expected to influence Use Behaviour.

4.3 Confirmatory Factor Analysis

Pearson Correlation Matrix shows the connection between two variables. The matrix mainly examines the observed variables to determine the association, relationship, and link between two variables simultaneously. However, the Pearson Correlation does not show the influence of one variable on another. The matrix solely assesses the directed link between two variables and the observed strength between those variables (Brown, 2015). For this reason, confirmatory factor analysis (CFA) has been assessed to draw genuine relationships and influence over latent constructs.

The measurement model test shows the relationship between the observed variables and the constructs. Besides, the CFA analysis also assesses the structural model, which will identify several correlations between the variables. The measurement model also validates the relationship by testing each hypothesized relationship separately to achieve model fit. Furthermore, measurement models like Chi-square and Goodness-of-Fit Index (GFI) have been used to assess the CFA analysis. The Chi-square is suggested to be divided by the degrees of freedom (df), and the model fit statistics are suggested to be approximate to the $p < .05$ significance level (Bentler, 1999). For instance, the probable ratio of two chi-square values is divided by their corresponding df.

Moreover, the GFI shows the ratio of fit, which is known as "squared residuals." The GFI value of .90 or above suggests a good model fit, whereas a value lower than .90 recommends improving the respective model. Furthermore, as CFA draws the causation relationship among variables, the SEM model is used to draw the influential relationships which create cause and effect.

4.4.1 CFA Model

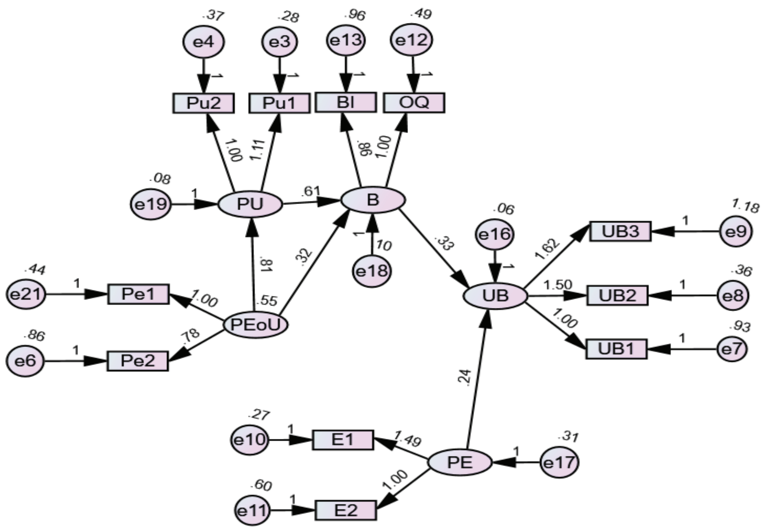

Figure 3. Confirmatory Factor analysis model

Instrument: The model is created by using both observed and unobserved variables. However, the unobserved variables also included two types of variables such as endogenous and exogenous variables. The observed variables are "Pu1= enhanced shopping", "Pu2=efficient decision", "E1= conversation enjoyment", "E2 = Customer service support", "BI= useful CC", "OQ= recommendations", "Pe1= ease of use", "Pe2= less effort", "UB1= usage duration", "UB2= usage regularity", and "UB3 = preference". The observed variable "recommendation" is counted as a variable of behavior intention in the model, as mentioned above. The unobserved endogenous variables are "PU= perceived usefulness", "UB= use behavior", and "PE = perceived enjoyment". However, the error term "e" is counted as an unobserved exogenous variable. "PEOU= perceived ease of use" is also counted as an exogenous variable.

4.4.2 CFA analysis

As depicted in Figure 3, the model has a chi-square value of 140.894 with a degree of freedom (df) of 39. The probability level of the chi-square is found with a significant level (p =.0000) which shows marginal fit. Besides, the value of GFI gained is 0.842, which shows that the value is tolerable but not proper for model fit, GFI> .90 (Pituch and Stevens, 2016). Besides, the AGFI value is .732, which shows a marginal model fit. The recommended value is AGFI ≥ .90. The CMIN/df value is 140.894/39, which results in 3.613, showing the model fit. The CFI value indicates the model complexity, which is recommended to be ≥ .90 showing the acceptable model fit (Whittaker, 2016). However, values of 95 or above are considered to be a superior fit. The demonstrated model shows a CFI value of .718, which shows poor model fit as the value is below the recommended level. The RMSEA value of a model is known as the "absolute fit index." The recommended value of RMSEA is less than .08. As our model results in the RMSEA value of 0.000, the model shows the best fit. Besides, the probability level is shown as p = 0.00, which shows the model does not fit properly as the suggested level is p >0.05. As the model shows poor fit, the model is modified to update the confirmatory model by removing unrelated latent variables and invalid indicators.

4.4.3 Updated CFA model

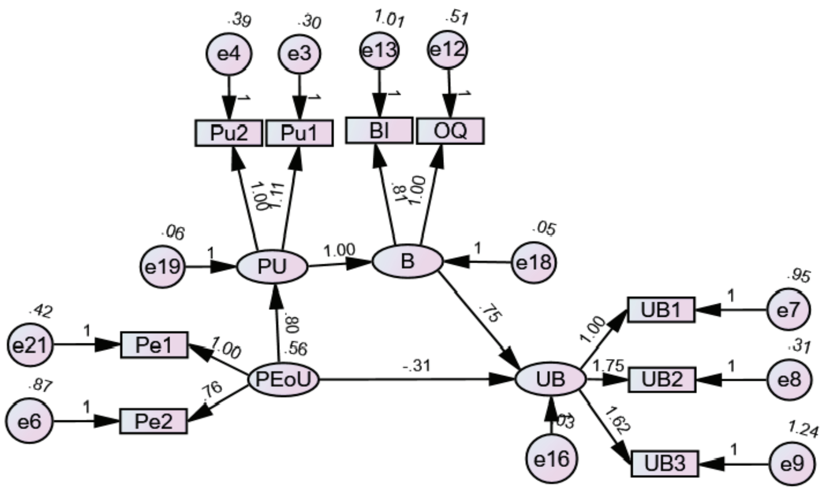

Figure 4 Updated Confirmatory model

Figure 4 shows that the updated model achieved model fit by the assessment of eight parameters of GFI. The assessment found that around eight parameters of GFI, seven parameters of GFI show proper model fit. Besides, the model also gains an SEM model fit representing relevance between data and model. However, the AGFI value shows a marginal fit.

4.4.4 Model Validity Test

The model validity is analyzed using the structural equation model (SEM) in the AMOS application 26.0 by completing a series of measurement tests. The model is analyzed by using three measurement tests, including "Absolute fit measurement," "Incremental fit measurement," and "Parsimonious-adjusted fit measurement" (Easterling, 1976). As the absolute fit measurement indicates the model fit between sample data and the proposed model, the index will demonstrate the superior model fit of the updated model (McDonald and Ho, 2002). Besides, the incremental fit measurement shows the comparative relation of the model by determining the relative fit index by comparing other measurement models with the baseline model (Miles and Shevlin, 2007). So, the comparative relation index will also be drawn for the proposed model. Moreover, Hooper et al. (2008) pointed out that a perfectly fitted model, also known as a saturated model, created based on sample data, often ironically creates a theoretically fit model showing better-fit indexes. Mulaik et al. (1989) suggested the parsimonious fit measurement encounters the possibility of irrational model fit. So, the parsimonious is also analyzed to justify the rationality of the model fit. For this reason, the fit, as mentioned earlier, measurements are well fitted for the study.

Table 3 Validity measurement index

Measurements	Recommended	Default Result	Description
Absolute Fit			
Chi-square		31.663	Good
CMIN/df	≤2.0	1.377	Good
Probability	>0.05	0.107	Good
GFI	>0.90	0.941	Good
RMSEA	<0.08	0.000	Good
Incremental Fit			
AGFI	>0.90	0.884	Marginal
CFI	>0.95	0.964	Good
Parsimonious-Adjusted Fit			
PCFI	>0.60	0.616	Good

Source: Primary Data Collection

The output of the evaluation of the model fit index is provided in Table (3). The Table shows that the model's chi-square value is 31.663 with a degree of freedom or df of 23, representing a proper model fit. The CMIN/df value is assessed as 1.377 ≤ 2.0, showing an absolute model fit. Besides, the probability level is 0.107 > 0.05, which also represents the absolute model fit. The value of GFI is found as 0.941 > 0.90, resulting in the proper model fit. However, the AGFI value was counted as 0.884, which is less than 0.90 showing a marginal model fit. The RMSEA value of the model, 0.000 < 0.08, represented an absolute model fit. Furthermore, the CFI value is also 0.964, which is more significant than 0.95 depicting a perfect model fit.

4.4.5 Hypothesis testing

The formula for the null and alternate hypothesis of the proposed variable is given below:

$H_0 = 0$; No Influence (accept H_0) and $H_1 \neq 0$; Influence (reject H_0)

Table 4: Hypothesis testing

Hypothesis	P Value	Outcome
H1: PU <--- PEoU	***	reject H_0
H2: B <--- PU	***	reject H_0
H3: UB <--- B	.219	accept H_0
H4: UB <--- PEoU	.550	accept H_0

Source: Primary Data Collection

In Table (4), the P-value, "***" shows that the probability of achieving a critical ratio is less than 0.001. The probability of the hypothesis value is recommended to be <0.05 to reject the null hypothesis. In the proposed model, the significance level of H1 is $p = 0.001<0.05$, which shows that perceived ease of use influences perceived usefulness. The significance level of H2 is also $p = 0.001<0.05$, which results in the connection of Behaviour intention to perceived usefulness. The H3 and H4 hypotheses are rejected as the p values are respectively 0.219 and 0.550, which are larger than the recommended 0.05. Furthermore, H5 is also rejected as it was deleted for modifying the confirmatory model.

4.4.6 Future Research Scope

Over the years, conversational commerce has developed from a novel force to an engine of growth in Bangladesh's evolving e-commerce ecosystem, with the very presence of research gaps, preventing its full utilization. These gaps need to be filled by conducting multifaceted studies and to strengthen the ecological system of conversational commerce. Initially learning and adapting to the language and cultural differences are very essential. NLP models have to continue to evolve in order to understand various Bangla dialects and colloquial phrases, all of which are popular in the country (Khan et al., 2023). This can be achieved through collective work of linguists and AI researchers by accumulating the datasets and modifying the models depending on the situation. Furthermore, culturally sensitive chatbot answers and product recommendations that are tailored to the user's needs require cultural anthropology and consumer behavior studies as input. Trust building and identification of adoption patterns are therefore both very important as wider acceptance of conversational commerce. Qualitative and quantitative research methods are invaluable in unearthing the desires, opinions, and expectations of the users. In the same way, the social influence of demographic characteristics and digital literacy levels on adoption rates requires cross-sectoral collaboration between sociologists, economists, as well as educational researchers. As discussed by Khan et al. (2017) frameworks for Human–computer interaction (HCI) researchers and data scientists must be created together in the first place to assess the effectiveness of trust-building strategies. Moreover, robust integration of current e-commerce platforms and broadening communication through other channels is necessary. Collaboration of computer scientists, software engineers, and platform owners is crucial to have an easy adaptation of conversational commerce to the existing platforms. In addition, working with marketing research and retail experts is essential because effective in-store experience improvement via chatbot interactions also requires this. Moreover, social media messaging and ride-hailing apps could be the areas where to focus on cross-platform integration. Therefore, cooperation of communication researchers, social media platforms, and service providers should be proposed to provide the best user experience. In doing this, the researchers will be able to make substantial contributions to the responsible growth and widespread adoption of conversational commerce in Bangladesh. Consequently, a more inclusive, user-centric and value-driven e-commerce industry will be constructed, where all stakeholder interests are taken into account.

5. Conclusions and Implications

The paper examines Bangladeshi customer behavior and conversational commerce devices. A postulated TAM 3 model is used to uncover and define chat and voice commerce's significant variables. The statistical profile predicted components of perceived utility, perceived ease of use, behavior intention, and user behavior based on empirical data from an online survey. The poll found that 63.2% of Bangladeshis use conversational commerce for online purchases and other purposes. 36.8% of respondents had never heard of or utilized conversational commerce for brand communication. 89.6% of online surfers choose Facebook for communication. The study also found that 89.6% of millennials prefer conversational commerce with businesses.

Conversational commerce delivers rapid engagement, automated offerings, personalised suggestions, and seamless customer service, which Bangladeshi consumers desire. The research indicated that perceived ease of use (PEoU) significantly affects perceived usefulness (PU) in conversational commerce. This supports Venkatesh and Bala's (2008) empirical investigation on PEoU in the TAM 3 paradigm. PEoU directly increases conversational commerce's perceived usefulness, according to the research. The study also found that perceived usefulness affects behavior intention. Perceived usefulness directly affects behavior intentions (BI) to use and embrace conversational commerce. However, perceived simplicity of use did not affect user behavior. Consumers' technology use preferences don't affect their opinion of ease of use. The research also demonstrated that behavioral purpose indirectly affects consumers' purchase behavior.

According to earlier research (Yang, 2010; Schierz et al., 2010), users' behavior intention (BI) drives conversational commerce adoption. Conversational commerce's value depends on how easy it is to use. Thus, chat and voice-based commerce may help firms meet consumer requirements and boost engagement. The survey found that most Bangladeshi customers are embracing conversational commerce owing to its perceived utility and simplicity of use. Conversational commerce includes drawbacks including "lack of consultation" and "the extra hassle during purchase." The paper advises organizations to improve conversational commerce customer care to boost customer happiness and adoption.

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