



Retail innovation through conversational commerce: Adoption intention of Gen Z consumers in Ahmedabad

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Abstract

Brand interactions with the consumers has being revolutionised by conversational commerce through the messaging apps like, Instagram and WhatsApp. Particularly, Generation Z consumers, who are distinguished by their peer-driven adoption and mobile-first behaviours, are found affected by this trend. For this generation of digital natives, shopping via messaging is a smooth and socially reinforced experience, and peer pressure is a major factor in adoption. By investigating the factors influencing urban Gen Z intention to adopt conversational commerce, this study fills a gap in the literature that has focused on e-commerce and mobile banking in emerging markets rather than chat-based retail. Using constructs from TAM and TPB, the model examines the effect of perceived cost, ease of use, personalisation, privacy and trust, perceived risk on attitude; and the effect of attitude, behavioural control, and subjective norms on adoption intention of conversational commerce. For this the data was gathered from 260 respondents of the age group between 18 to 25, and who had previous experience in messaging-based retail. The data was analysed using partial least squares structural equation modelling. The findings show the significant effect of perceived risk, privacy and trust, and ease of use on consumer attitudes, attitude was not found predicting the adoption intention of the respondents. Further, perceived behavioural control and subjective normal were observed as the major factors affecting the behavioural intentions, highlighting the importance of peer influence and self-efficacy in collectivist settings. The study further provides valuable discussions and implications for the factors affecting conversational commerce adoption by the Gen Z.

Keywords: Conversational commerce, messaging applications, adoption intention, generation Z, TAM, TPB

Introduction

Conversational commerce, defined as the integration of messaging platforms with transactional retail functions has fundamentally transformed digital retail interactions by merging communication and commerce within unified conversational ecosystems. Platforms such as WhatsApp, Instagram, and Telegram now enable catalogue browsing, product recommendations, order placement, payment processing, and post-purchase support within a single conversational interface. This evolution reflects a broader transition from static, website-based e-commerce to interactive, AI-enabled, dialogue-driven retail experiences. Recent research highlights that conversational agents and AI-driven shopping assistants significantly enhance perceived usefulness and customer engagement, thereby strengthening adoption intentions (Singh *et al.*, 2024; Hamedani *et al.*, 2025) [17, 34].

Globally, conversational commerce is experiencing rapid expansion, driven by mobile-first markets and AI integration. India represents one of the most dynamic growth environments due to its expanding digital infrastructure, widespread smartphone penetration, and strong uptake of messaging platforms for business transactions. Studies on chatbot-based commerce and AI retail assistants indicate that trust, personalization, and ease of use are central to user adoption, particularly among younger demographics (Jyothsna & Kryvinska, 2024; Foroughi *et al.*, 2025) [13, 21]. Gen Z consumers characterized by digital nativity, immediacy expectations, and preference for conversational interfaces are especially receptive to AI-enabled shopping environments (Choudhary & Ahuja, 2025) [6].

The theoretical foundation for understanding conversational commerce adoption is grounded in established technology acceptance models. The Technology Acceptance Model (TAM) emphasizes perceived usefulness (PU) and perceived ease of use (PEOU) as primary determinants of behavioral intention (Davis, 1989) [7]. Extensions of TAM and the Unified Theory of Acceptance and Use of Technology (UTAUT) incorporate additional constructs such as social influence, facilitating conditions, perceived cost, and trust (Venkatesh *et al.*, 2003) [42]. Contemporary studies applying these frameworks to AI chatbots and digital shopping assistants demonstrate that trust frequently acts as a mediating variable between technological attributes and adoption intention (Singh *et al.*, 2024; Bansal *et al.*, 2026) [4, 34]. Furthermore, perceived risk and privacy concerns continue to moderate adoption decisions in emerging digital markets (Saklani & Kala, 2025) [33].

Although the existing literature underscores the importance of trust, convenience, personalization, and technological readiness, most empirical investigations focus on Western contexts or aggregate national samples. Limited research addresses localized urban ecosystems within India, where cultural norms, infrastructural conditions, and consumer behavior patterns differ significantly. Ahmedabad, one of Gujarat's fastest-growing metropolitan cities, represents a particularly relevant context. Its expanding startup ecosystem, strong SME presence, and digitally active youth population make it an ideal environment to examine conversational commerce adoption dynamics.

Gen Z consumers in Ahmedabad exhibit high levels of smartphone dependency, social media engagement, and openness to AI-mediated interactions. Yet, there remains a

lack of empirical evidence examining how constructs such as trust, perceived usefulness, perceived ease of use, perceived cost, and social influence jointly shape their adoption intentions in conversational commerce environments. Addressing this gap is essential to refine theoretical extensions of TAM and UTAUT in regional digital commerce settings.

Accordingly, this study investigates the determinants of conversational commerce adoption among Gen Z consumers in Ahmedabad. By contextualizing established technology acceptance constructs within a localized urban ecosystem, the research contributes to both theoretical advancement and managerial practice. The findings are expected to offer actionable insights for retailers, digital marketers, and platform developers seeking to optimize conversational strategies in India's evolving digital retail landscape. Moreover, the study contributes to ongoing discourse on AI-enabled retail innovation by providing region-specific empirical evidence.

The remainder of the paper is structured as follows: Section 2 reviews the relevant literature; Section 3 outlines the research methodology; Section 4 presents the empirical findings; Section 5 discusses theoretical and managerial implications; and Section 6 concludes with recommendations for future research.

Literature Review

1. Factors affecting attitude of consumers

Empirical research has consistently positioned attitude as a central mediating construct between technological perceptions and behavioral intention in conversational commerce environments. Drawing from TAM, TPB, and UTAUT extensions, studies demonstrate that perceived usefulness, perceived ease of use, trust, social influence, perceived risk, personalization, and cost perceptions significantly shape users' attitudes toward AI-powered chatbots and conversational platforms (Singh *et al.*, 2024; Addula *et al.*, 2025; Jyothsna & Kryvinska, 2024) ^[1, 21, 34]. In emerging markets such as India, contextual variables including digital literacy, infrastructural reliability, and price sensitivity moderate the relationship between these constructs and attitude (Saklani & Kala, 2025; Meena & Sarabhai, 2024) ^[28, 33]. Among Gen Z consumers, hedonic motivation, anthropomorphic chatbot features, and immediacy expectations further strengthen positive attitudinal formation (Choudhary & Ahuja, 2025; Hamedani *et al.*, 2025) ^[6, 17].

The following literature review synthesizes key determinants of attitude toward conversational commerce, providing theoretical grounding for hypothesis development in the Ahmedabad Gen Z context.

Perceived ease of use (PEOU) refers to the degree to which using a system is free of effort (Davis, 1989) ^[7]. Conversational interfaces inherently reduce cognitive effort by mimicking natural dialogue. Recent chatbot studies confirm that ease of interaction improves user satisfaction and fosters favorable attitudes (Jyothsna & Kryvinska, 2024) ^[21]. Studies have observed that ease of use indirectly shapes behavioural intention through attitude (Nigam & Yamini, 2022; Doshi, 2018) ^[8, 31, 43] and trust (Singh *et al.*, 2024) ^[34]. For digital-native Gen Z consumers, intuitive UI and conversational clarity reduce friction and strengthen positive evaluations of the platform.

Trust is a critical determinant in AI-mediated environments where automation replaces human interaction. It encompasses reliability, data security, and perceived integrity. Addula *et al.* (2025) ^[1] demonstrated that trust significantly mediates the relationship between chatbot attributes and consumer attitude. Saklani and Kala (2025) ^[33] similarly found that chatbot satisfaction and continuance intention are highly dependent on trust perceptions. In emerging economies, trust plays an even more decisive role due to concerns over privacy and transaction security (Singh *et al.*, 2024) ^[34]. For Gen Z users in Ahmedabad, who frequently transact via WhatsApp and Instagram, trust in platform security and vendor authenticity may substantially shape attitudinal formation.

Perceived risk refers to the potential for financial, privacy, or performance loss associated with system usage. Research in AI-enabled commerce consistently finds that risk perceptions negatively influence consumer evaluations (Addula *et al.*, 2025) ^[1]. In chatbot-based banking contexts, perceived risk significantly reduced favorable attitudes and continuance intention (Saklani & Kala, 2025) ^[33]. Privacy concerns are particularly salient in mobile-first economies where personal data exchange is frequent (Jyothsna & Kryvinska, 2024) ^[21]. Given India's growing digital payment ecosystem, risk perceptions may negatively shape Gen Z attitudes toward conversational transactions.

Within TAM extensions and privacy calculus theory, privacy concerns are conceptualized as perceived risks that influence attitudinal evaluation before behavioral intention develops. Kaur, Dhir, and Talwar (2024) found that privacy concerns significantly reduced positive attitudes toward AI-enabled retail chatbots, particularly among younger consumers who are more aware of algorithmic data usage. Similarly, Hossain *et al.* (2025) reported that privacy anxiety negatively influenced attitude toward conversational AI, with trust acting as a partial mediator. Gen Z users tend to evaluate conversational commerce platforms based on transparency of data policies and perceived control over information sharing (Adeola *et al.*, 2024). When privacy safeguards are perceived as strong, users demonstrate more favorable attitudes toward AI-mediated transactions.

Conversational commerce leverages AI to deliver tailored recommendations and human-like interactions (Personalization and Anthropomorphic). Anthropomorphic cues (e.g., conversational tone, emojis, human names) increase emotional engagement and perceived warmth (Hamedani *et al.*, 2025) ^[17]. Addula *et al.* (2025) ^[1] found that personalized chatbot interactions significantly improved consumer attitude. For Gen Z users who value experiential shopping, personalization enhances perceived enjoyment and relational closeness.

Price sensitivity remains a defining characteristic of Indian digital consumers. Perceived cost includes transaction charges, data usage, and perceived value for money. Meena and Sarabhai (2024) ^[28] found that economic considerations significantly influenced attitude in mobile commerce settings. In conversational commerce, where transactions often occur through low-cost messaging apps, favorable cost perceptions may strengthen positive attitudes. Based on above we hypothesised that:

H1: Perceived ease of use positively influences Gen Z consumers' attitude toward conversational commerce.

H2: Trust positively influences Gen Z consumers' attitude toward conversational commerce.

- H3:** Perceived risk negatively influences Gen Z consumers' attitude toward conversational commerce.
- H4:** Privacy concern negatively influence Gen Z consumers' attitude toward conversational commerce.
- H5:** Perceived personalization positively influences Gen Z consumers' attitude toward conversational commerce.
- H6:** Favourable cost perception positively influences Gen Z consumers' attitude toward conversational commerce.

2. Factors affecting adoption intention of consumers

The Theory of Planned Behavior (TPB) posits that attitude, subjective norms, and perceived behavioral control (PBC) jointly predict behavioral intention (Ajzen, 1991) [3]. In digital commerce contexts, particularly social commerce, conversational commerce, and AI chatbot adoption, TPB has consistently demonstrated strong explanatory power. Recent empirical studies confirm that positive attitudes toward AI chatbots, favorable social influence, and higher perceived control over technology significantly increase consumers' intention to adopt conversational commerce platforms. Meta-analytic evidence in social commerce contexts indicates that TPB constructs remain robust predictors of purchase and usage intentions across digital platforms (Leong *et al.*, 2023) [23]. Emerging chatbot-specific research further shows that these determinants operate similarly in conversational interfaces embedded in e-commerce environments (Kim *et al.*, 2023; Tai *et al.*, 2024; Naji *et al.*, 2025) [22, 30, 37].

Attitude reflects an individual's positive or negative evaluation of performing a behavior (Doshi, 2021) [9]. In conversational commerce, attitude is shaped by perceived usefulness, enjoyment, trust, efficiency, and personalization of AI chatbots. Studies show that favorable attitudes significantly predict adoption intention of AI-driven chatbots in e-commerce (Yue & Ng, 2024; Lopes *et al.*, 2024) [24, 44]. Similarly, Tan *et al.* (2024) found that attitude directly influences consumers' intention to use m-commerce chatbots. Research in hotel chatbot applications also demonstrates that positive evaluations increase behavioral intention (Islam *et al.*, 2024) [20].

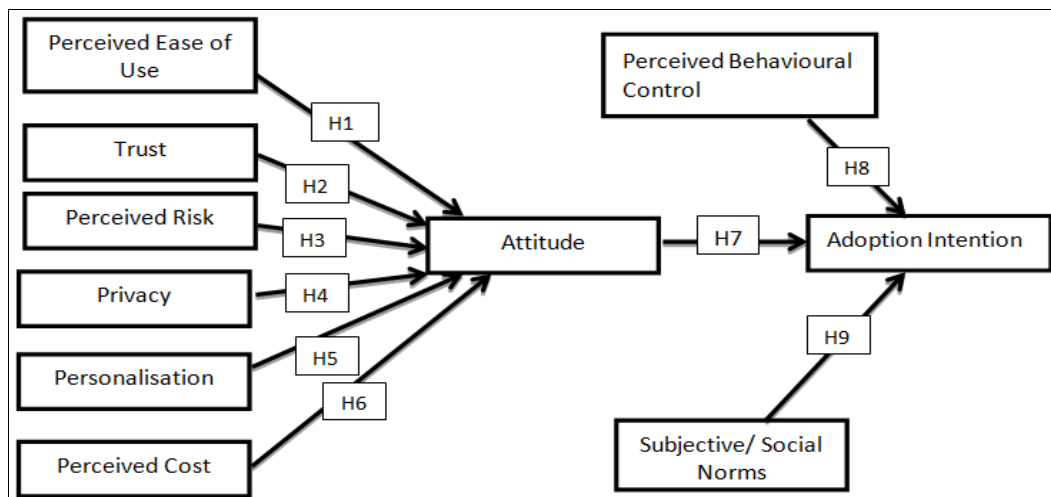
In conversational commerce specifically, consumer perception research indicates that positive beliefs about convenience, responsiveness, and interactive engagement strengthen favorable attitudes, leading to higher adoption intention (Ahmed & Gopal, 2025) [2]. Perceived behavioral control reflects the perceived ease or

difficulty of performing a behavior and is closely linked to self-efficacy and digital competence. In AI chatbot adoption research, PBC consistently predicts behavioral intention (Tai *et al.*, 2024; Naji *et al.*, 2025) [30, 37]. Consumers who perceive greater digital literacy, technological familiarity, and control over chatbot interactions demonstrate stronger adoption intention (Trang, 2021) [39]. Studies integrating TPB into AI e-commerce contexts show that when users believe they possess adequate resources, knowledge, and technical capability, their likelihood of adopting conversational agents increases significantly (Iqbal *et al.*, 2024; Alnefaie, 2024) [19]. In conversational commerce settings, ease of use and perceived control over chatbot interaction flow further reinforce behavioral intention (Lopes *et al.*, 2024) [24].

Subjective norms refer to perceived social pressure from important referents (e.g., peers, family, influencers) to perform or avoid a behaviour. In digital environments, social influence is amplified through social media integration and network effects. Empirical studies confirm that subjective norms significantly affect m-Commerce adoption (yamini, 2022) [43] as well as chatbot adoption intention (Kim *et al.*, 2023; Trang, 2021) [22, 39]. Research in AI commerce contexts indicates that consumers are more likely to adopt conversational commerce when they perceive that others in their social circle support or use such technologies (Uddin & Low, 2024; Naji *et al.*, 2025) [30, 40]. Further, meta-analytic evidence in social commerce further demonstrates that subjective norms exert both direct and indirect effects on behavioral intention (Leong *et al.*, 2023) [23]. Although some studies find weaker effects compared to attitude, the social commerce context strengthens normative influence due to embedded social interaction mechanisms. Hence we hypothesised that:

- H7:** Attitude positively influences adoption intention of Gen Z consumers' toward conversational commerce.
- H8:** Perceived behavioural control positively influences adoption intention of Gen Z consumers' toward conversational commerce.
- H9:** Subjective/social norms positively influences adoption intention of Gen Z consumers' toward conversational commerce.

Based on the above review of literature we proposed the conceptual model for the study. The conceptual model is given in figure number 1.



Source: The model is author-developed based on the literature review.

Fig 1: Research Model

Research Methodology

This study utilizes a quantitative, cross-sectional research design to investigate the determinants affecting the adoption intention of conversational commerce among Generation Z consumers in Ahmedabad. A non-probability purposive sampling method was utilized to select respondents aged 18–25 who have previously participated in chat-based retail transactions through messaging applications such as WhatsApp, Instagram, or Telegram. This method is appropriate due to the study's emphasis on urban Gen Z consumers, a demographic recognized for significant digital engagement and mobile-first tendencies. Ahmedabad was chosen as the geographic focus because it has both strong traditional retail and quick digital integration, making it a great urban microcosm for studying how conversational commerce is being used. The city's entrepreneurial culture and widespread use of messaging platforms for commerce by local businesses further validate its relevance. The final sample comprised 260 valid responses, statistically sufficient for Structural Equation Modelling (SEM) employing Partial Least Squares (PLS). Hair *et al.* (2019) [16] suggest that the sample size should be at least 10

times the most indicators used to measure one construct. In this study, the construct Perceived Behavioural Control has the most indicators (8 items), which means that the minimum sample size should be 80. The sample size of 260 is higher than this threshold, which means that the model can be estimated accurately and the results can be applied to other situations.

Structured questionnaire was used to gather the demographic and relevant data for the study, it was available both online and offline. The questionnaire was constructed utilizing validated scales modified from previous research and tailored for conversational commerce. There were nine constructs in the questionnaire, and each one was measured on a Likert-type scale from 1 (Strongly Disagree) to 5 (Strongly Agree). The details of the construct and scales are given in table 1. Further, we reached out to people through university networks, social media groups, and local retail communities. WhatsApp and Instagram were used to send out online forms, and offline data was gathered at college campuses and urban retail hubs.

Table 1: Sources of Variables in Questionnaires and Key References

Construct	Key References
Perceived Ease of Use (PEOU)	Davis (1989) [7]; Venkatesh & Davis (2000) [41]
Trust	Gefen <i>et al.</i> (2003) [14]; McKnight <i>et al.</i> (2002) [27]
Perceived Risk	Bauer (1960) [5], Featherman & Pavlou (2003) [10]
Privacy	Smith <i>et al.</i> (1996) [35]; Malhotra <i>et al.</i> (2014) [26]
Personalisation	Tam & Ho (2006); Xu <i>et al.</i> (2012)
Perceived Cost	Monroe (1973) [29]; Zeithaml (1988) [45]
Attitude	Fishbein & Ajzen (1975); Ajzen (1991) [3]
Perceived Behavioural Control	Ajzen (1991) [3]; Taylor & Todd (1995) [38]
Subjective Norms	Fishbein & Ajzen (1977) [11]; Ajzen (1991) [3]
Adoption Intention	Ajzen, I. (1991) [3]

Source: Author's own creation

Table 2 presents the demographic profile of the 260 respondents included in the study.

The demographic detail of the respondents are given in table number 2. The demographic details of the respondents was collected in terms of age, gender, occupation, and family income. Understanding the demographic characteristics of the sample is essential, as they offers a comprehensive overview of the sample structure. Further, this information ensures transparency regarding the representativeness of the data.

Table 2: Demographic Details of the Respondents

Demography		Respondents (260)	Percentage
Age	18-21	126	48.46
	22-25	134	51.54
Gender	Male	126	48.46
	Female	134	51.54
Occupation	Student	99	38.08
	Service	95	36.54
	Self-Employed	66	25.38
Family Income (Rs.)	<6 Lakh	87	33.46
	6-9 Lakh	87	33.46
	9-12 Lakh	49	18.85
	>12 Lakh	37	14.23

Source: Author's own creation

Data Analysis and Interpretation

This study employed Partial Least Squares Structural Equation Modeling (PLS-SEM) to analyze the proposed research model and test the hypothesized relationships among constructs. PLS-SEM was selected due to its suitability for predictive research, complex models, and situations involving relatively small sample sizes or non-normal data distributions. The analysis was conducted using 4.0 SmartPLS. Table 3 presents the results of the construct reliability and validity assessment. Indicator reliability was assessed through factor loadings. According to Hair *et al.* (2019) [16] outer loadings should ideally exceed 0.70, indicating that the construct explains more than 50% of the indicator's variance.

While loadings between 0.40 and 0.70 may be retained if composite reliability and AVE remain adequate (Hair *et al.*, 2019) [16]. Convergent validity was evaluated using Average Variance Extracted (AVE). As suggested by Fornell & Larcker (1981) [12], AVE values should exceed 0.50 to indicate that the construct explains more than half of the variance of its indicators. All constructs under study satisfy this criterion. Further, all the multi-item constructs demonstrate adequate composite reliability, with values ranging from 0.772 (Subjective Norms) to 0.985 (Perceived Behavioural Control). These results confirm strong internal consistency across constructs as they were above 0.70 (Hair

et al., 2019) [16]. Cronbach's alpha values also exceed the recommended threshold of 0.70 for most constructs. While Cronbach's alpha is considered a conservative measure in PLS-SEM, composite reliability is preferred due

to its ability to account for differing indicator loadings (Henseler et al., 2009). Therefore, the construct can still be considered reliable given its acceptable CR and AVE values.

Table 3: Construct Reliability and Validity

Constructs	Items	Factor Loading	AVE	Composite Reliability	Cronbach Alpha
PEOU	PEOU1-PEOU2	.943-.952	0.898	0.946	0.886
PR	PR1-PR3	.921-.944	0.872	0.953	0.927
Trust	Trust1-Trust2	.975-.980	0.956	0.977	0.954
Privacy	Pry1-Pry3	.947-.958	0.907	0.967	0.949
Per	Per1-Per3	.629-.842	0.570	0.797	0.674
PC	PC1-PC4	.872-.921	0.804	0.942	0.922
Att	Att1-Att4	.794-.839	0.678	0.894	0.842
PBC	PBC1-PBC8	.919-.965	0.891	0.985	0.984
SN	SN1-SN2	.552-.995	0.647	0.772	0.632
Ado	Ado1-Ado6	.699-.875	0.630	0.911	0.882

Abbreviations: Perceived Ease of Use (PEOU), Perceived Risk (PR), Personalisation (Per), Perceived Cost (PC), Subjective Norm (SN), Attitude (Att), Perceived Behavioural Control (PBC), Adoption (Ado)

Source: Author's own creation

Discriminant validity was assessed using the Fornell-Larcker criterion and the heterotrait-monotrait ratio (HTMT), as recommended in PLS-SEM literature. According to the Fornell-Larcker criterion, discriminant validity is established when the square root of the Average Variance Extracted (AVE) of each construct exceeds its correlations with other constructs in the model (Claes Fornell & David F. Larcker, 1981) [12]. As presented in Table 4, the diagonal values (square roots of AVE) for all constructs, PEOU (0.948), PR (0.934), Trust (0.978), Privacy (0.952), Personalisation (0.755), Perceived Cost (0.897), Attitude (0.823), PBC (0.944), Subjective Norm (0.804), and Adoption (0.794) are greater than their respective inter-construct correlations. This indicates that

each construct shares more variance with its own indicators than with other latent constructs, thereby satisfying the Fornell-Larcker criterion. Additionally, discriminant validity was examined using the HTMT ratio, which is considered a more stringent and reliable approach for detecting lack of discriminant validity (Jörg Henseler et al., 2015) [18]. All HTMT values reported above the diagonal are below the recommended threshold of 0.90, indicating adequate discriminant validity among the constructs. Although relatively higher HTMT values were observed between Trust and Privacy (0.896), and between Privacy and Personalisation (0.786), these values remain within acceptable limits, suggesting that the constructs are empirically distinct despite conceptual proximity.

Table 4: Discriminant Validity

	PEOU	PR	Trust	Privacy	Per	PC	Att	PBC	SN	Ado
PEOU	0.948	0.097	0.270	0.263	0.258	0.145	0.363	0.037	0.142	0.123
PR	-0.087	0.934	0.110	0.108	0.108	0.051	0.170	0.024	0.258	0.064
Trust	0.248	-0.105	0.978	0.896	0.768	0.123	0.299	0.205	0.138	0.132
Privacy	0.242	-0.106	0.949	0.952	0.786	0.155	0.287	0.180	0.160	0.135
Per	0.245	-0.108	0.729	0.741	0.755	0.168	0.275	0.104	0.156	0.146
PC	-0.132	-0.022	-0.114	-0.145	-0.130	0.897	0.120	0.024	0.291	0.668
Att	0.317	-0.153	0.274	0.266	0.255	-0.114	0.823	0.053	0.171	0.097
PBC	0.050	-0.017	0.232	0.210	0.097	-0.022	-0.006	0.944	0.038	0.056
SN	-0.103	0.164	-0.104	-0.130	-0.115	0.291	0.036	-0.012	0.804	0.516
Ado	-0.111	0.001	-0.123	-0.126	-0.111	0.600	-0.057	-0.064	0.573	0.794

Abbreviations: Perceived Ease of Use (PEOU), Perceived Risk (PR), Personalisation (Per), Perceived Cost (PC), Subjective Norm (SN), Attitude (Att), Perceived Behavioural Control (PBC), Adoption (Ado)

Note: Diagonal, Bold, and Italicized are the square roots of the AVE. Below the diagonal elements are the correlations between the construct's values. Above the diagonal elements are the heterotrait-monotrait ratio of correlations values

Source: Author's own creation based on PLS -SEM results

Table 5 presents the structural model results, including standardized path coefficients (β), standard deviations, p-values, confidence intervals, and hypothesis decisions. The significance of the structural relationships was assessed using bootstrapping procedures in PLS-SEM, with significance determined at $p < 0.10$, $p < 0.05$, and $p < 0.01$ levels.

The results indicate that Perceived Ease of Use (PEOU) has a positive and significant effect on Attitude ($\beta = 0.247$, $p = 0.001$), supporting H1. This suggests that when conversational commerce platforms are perceived as easy to

use, Gen Z consumers develop a more favorable attitude toward their usage. Similarly, Trust positively influences Attitude ($\beta = 0.159$, $p = 0.045$), supporting H2, indicating that greater confidence in the platform enhances positive consumer evaluations.

In contrast, Perceived Risk (PR) demonstrates a significant negative impact on Attitude ($\beta = -0.110$, $p = 0.000$), supporting H3. This implies that higher perceived uncertainty or risk reduces favorable attitudes toward conversational commerce. Privacy shows a marginally significant negative effect on Attitude ($\beta = -0.019$, $p =$

0.092), supporting H4 at the 10% level, suggesting that privacy concerns may slightly weaken positive attitudes. Personalisation (Per) has a positive and significant influence on Attitude ($\beta = 0.073$, $p = 0.049$), supporting H5, indicating that customized interactions enhance user perceptions. However, Perceived Cost (PC) does not significantly influence Attitude ($\beta = -0.058$, $p = 0.299$), leading to the rejection of H6. Regarding adoption, Attitude significantly and positively

affects Adoption (Ado) ($\beta = 0.278$, $p = 0.012$), supporting H7. This confirms that favorable attitudes translate into stronger adoption intentions. Subjective Norm (SN) exhibits the strongest positive effect on Adoption ($\beta = 0.575$, $p = 0.000$), supporting H9, highlighting the critical role of social influence in shaping Gen Z adoption behavior. Conversely, Perceived Behavioural Control (PBC) does not significantly affect Adoption ($\beta = -0.057$, $p = 0.425$), resulting in the rejection of H8.

Table IV: Hypotheses Testing Results

Hypothesis Relationship	Std. Beta	STDEV	P Values	Confidence Interval		Decision
				2.50%	97.50%	
H1: PEOU ->Att	0.247	0.073	0.001***	0.091	0.365	Supported
H2: Trust ->Att	0.159	0.213	0.045**	-0.214	-0.604	Supported
H3: PR ->Att	-0.11	0.025	0.000***	-0.153	-0.057	Supported
H4: Privacy ->Att	-0.019	0.199	0.092*	0.240	0.353	Supported
H5: Per->Att	0.073	0.106	0.049**	-0.220	0.220	Supported
H6: PC ->Att	-0.058	0.056	0.299	-0.133	0.148	Rejected
H7: Att -> Ado	0.278	0.051	0.012**	-0.176	-0.019	Supported
H8: PBC -> Ado	-0.057	0.071	0.425	-0.145	0.140	Rejected
H9: SN -> Ado	0.575	0.06	0.000***	0.435	0.681	Supported
Abbreviations: Perceived Ease of Use (PEOU), Perceived Risk (PR), Personalisation (Per), Perceived Cost (PC), Subjective Norm (SN), Attitude (Att), Perceived Behavioural Control (PBC), Adoption (Ado)						
Note: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$						

Source: Author's own creation based on PLS -SEM results

The explanatory power of the structural model was evaluated using the coefficient of determination (R^2). The R^2 value for Adoption is 0.338, indicating that 33.8% of the variance in adoption intention is explained by its antecedent constructs, namely Attitude, Subjective Norm, and Perceived Behavioural Control. According to established guidelines in PLS-SEM, R^2 values of approximately 0.25, 0.50, and 0.75 can be described as weak, moderate, and substantial, respectively (Joseph F. Hair Jr. *et al.*, 2019) [16]. Therefore, the R^2 value for Adoption suggests moderate explanatory power, implying that the model provides a reasonable explanation of Gen Z consumers' adoption behavior in the context of conversational commerce. In contrast, the R^2 value for Attitude is 0.159, which indicates that 15.9% of the variance in attitude is explained by its predictors (PEOU, Trust, Perceived Risk, Privacy, Personalisation, and Perceived Cost). This level of R^2 can be interpreted as weak to moderate, suggesting that while the included constructs significantly contribute to attitude formation, additional factors not captured in the model may also influence consumers' attitudinal responses.

The model's predictive relevance was further assessed using the Stone-Geisser Q^2 value obtained through the blindfolding procedure. The Q^2 value for Adoption is 0.189, and for Attitude, it is 0.088. A Q^2 value greater than zero indicates that the model has predictive relevance for a given endogenous construct (Michael Stone, 1974; Seymour Geisser, 1975) [15, 36]. Based on commonly used thresholds (0.02 = small, 0.15 = medium, 0.35 = large), the Q^2 value for Adoption demonstrates moderate predictive relevance, whereas the Q^2 value for Attitude reflects small but acceptable predictive relevance (Christian M. Ringle *et al.*, 2020) [32].

Findings and Conclusions

Findings

The structural model results reveal that Attitude and Subjective Norm (SN) are the most influential determinants

of Adoption, with SN ($\beta = 0.575$, $p < 0.01$) emerging as the strongest predictor. This indicates that social influence plays a critical role in shaping Gen Z consumers' adoption of conversational commerce, aligning with the theoretical assumptions of the Theory of Planned Behaviour. Attitude also significantly influences Adoption ($\beta = 0.278$, $p < 0.05$), confirming that favourable evaluations of conversational commerce translate into stronger behavioral intentions. However, Perceived Behavioural Control (PBC) does not significantly influence Adoption, suggesting that Gen Z consumers may not perceive capability or resource constraints as major barriers in digital commerce contexts.

Regarding the determinants of Attitude, Perceived Ease of Use (PEOU) ($\beta = 0.247$, $p < 0.01$), Trust ($\beta = 0.159$, $p < 0.05$), and Personalisation ($\beta = 0.073$, $p < 0.05$) positively and significantly influence Attitude. These findings support technology acceptance logic, particularly the Technology Acceptance Model, which posits that ease of use enhances favorable user evaluations. Conversely, Perceived Risk (PR) negatively affects Attitude ($\beta = -0.110$, $p < 0.01$), indicating that higher uncertainty reduces positive perceptions. Privacy shows a marginal negative effect, while Perceived Cost (PC) does not significantly affect Attitude.

The R^2 values indicate moderate explanatory power for Adoption (0.338) and weak-to-moderate explanatory power for Attitude (0.159), consistent with recommended benchmarks in PLS-SEM research (Joe F. Hair *et al.*, 2019) [16]. The Q^2 values (> 0) confirm predictive relevance of the model.

Conclusions

The study concludes that social influence and attitudinal factors are central to understanding Gen Z consumers' adoption of conversational commerce. While cognitive factors such as ease of use and trust shape positive attitudes, social norms exert the strongest direct effect on adoption intention. This suggests that Gen Z consumers are highly

responsive to peer opinions, digital communities, and influencer-driven recommendations.

Risk perceptions and privacy concerns negatively influence attitudes, indicating that security and transparency remain critical in digital retail environments. The insignificant role of perceived cost and PBC suggests that affordability and perceived control may not be primary adoption barriers in this demographic, likely due to their familiarity with digital technologies. Overall, the findings validate the integrated application of the Theory of Planned Behaviour and the Technology Acceptance Model in explaining conversational commerce adoption.

Limitations and future directions

This study provides important insights into the determinants of conversational commerce adoption among Gen Z consumers in Ahmedabad; however, several limitations must be acknowledged. First, the use of non-probability purposive sampling, while appropriate for targeting digitally active youth, restricts the generalizability of the findings beyond the selected urban demographic. The sample consisted exclusively of respondents aged 18–25 with prior experience in chat-based commerce, thereby excluding younger members of Gen Z and individuals unfamiliar with such platforms. Additionally, the geographic focus on Ahmedabad, a Tier-1 city characterized by relatively advanced digital infrastructure and socio-cultural dynamics, may limit the applicability of results to Tier-2 or Tier-3 cities where technology access, peer influence patterns, and digital trust levels may differ. Second, the study relied on self-reported data collected through structured questionnaires, which may be subject to social desirability bias and recall inaccuracies. Although the measurement model demonstrated acceptable reliability and validity and the structural model showed moderate explanatory and predictive power consistent with PLS-SEM guidelines (Joe F. Hair *et al.*, 2019) ^[16], the cross-sectional research design restricts causal inference. The relatively modest R² value for Attitude and the comparatively weaker effect of Attitude on Adoption suggest that unexamined moderating or mediating variables—such as peer density, digital literacy, platform familiarity, perceived enjoyment, or linguistic comfort—may influence behavioural outcomes.

Future research should therefore adopt longitudinal designs to track changes in consumer perceptions and behavioural intentions over time, thereby strengthening causal interpretation. Incorporating qualitative approaches, such as in-depth interviews or focus groups, could provide richer insights into the psychological motivations and barriers underlying conversational commerce usage. Expanding the geographic scope to include semi-urban and rural youth would improve the contextual robustness of findings and reflect India's diverse digital ecosystem. Comparative studies across generational cohorts, such as Millennials and Gen Z, may further illuminate differences in technology adoption patterns. Additionally, future models could integrate constructs from the Technology Acceptance Model and the Theory of Planned Behaviour with emerging variables such as influencer credibility, habit formation, and social media engagement intensity to enhance explanatory power. Such extensions would contribute to a more comprehensive understanding of conversational commerce adoption within India's evolving retail landscape.

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