

EVALUATING THE IMPACT OF CHATBOT RESPONSIVENESS ON CONSUMER EXPERIENCE IN THE INDIAN AUTOMOBILE INDUSTRY

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Abstract: *The present research aims to examine the consequences of chatbot technology on consumer experience and satisfaction in the context of the automobile industry in India with an emphasis on the responsiveness (RSP) and reliability (REL). Applying confirmatory factor analysis (CFA) and structural equation modeling (SEM), the study aims to investigate how these factors affect customer experience (CEXP) and the customer satisfaction (CSAT). Exploring the results of the study, it is evident that RSP and REL significantly improve CEXP. Additionally, it is evident that CEXP mediate the relationship between RSP, REL and the CSAT. The survey was administered to 401 respondents and the data were cross-checked to provide reliability in the analysis. The results of the model fit indices support the fit of the proposed model, confirming the significance of positive chatbot interactions in attaining high levels of customer satisfaction. This article also adds value to the current literature by examining the reliability and responsiveness of chatbots in achieving digital consumer engagement. The study provides useful implications for the automobile sector, with overall enhancements of these aspects of contributing to enhanced client experiences and better customer retention. This research could be extended further as subsequent studies by incorporating other variables like the personalisation of the chatbot and culture.*

Keywords: *Automobile Industry, Pro-Activism, Responsiveness, Reliability, Consumer Experience, Chatbots, Customer Satisfaction, Analytical Tools, Structural Equation Modelling, Indian Automobile Industry*

INTRODUCTION

The automobile industry in India has been realising its potential in the country's economic development and has been giving a boost to the GDP and employment. In the past ten years, this industry has enjoyed rapid development due to enhanced consumer needs, elevated urban population and enhanced middle-income group income. In this case, the sector consists of a wide number of them, including international ones and small local ones, all seeking to gain a share of the diverse market in India. Nonetheless, the nature of the business has changed and remains so given the high levels of competition that have forced enterprises to adapt more often, particularly on the customer interface front (National Investment Promotion & Facilitation Agency, n. d.).

Perhaps one of the most profound trends over the years has been the adoption of AI technologies, particularly chatbots, into customer touchpoints. The automobile industry has now adopted chatbots to play a useful role in automating simple questions, aiding in the selection of car models, setting up test

drives and managing post-purchase services (Yun & Park, 2022). AI-incorporated chatbots have allowed companies to provide prompt and individualised engagements, which are crucial in a setting where the decisions by customers are based on the quality of information that is available to them and the time that information is provided to them (Tran, Pallant & Johnson, 2021).

Chatbots are being used in the current generation as a way of having efficient communication between the automobile companies and its customers, especially in India. For instance, websites and mobile applications have common features to place, for example, many companies have integrated artificial intelligence-based chatbots that answer customers' queries about products and services, provide information about products and services, and even help users make bookings online. This trend goes in line with the worldwide shift to the digital paradigm and depicts the industry's readiness to improve the customer experience through advanced technologies (Rane, Rane & Choudhary, 2013).

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In the current world, the level of competition has reached a high level where customer satisfaction and experience are critical success factors. The automobile industry is an example of an industry that faces intense competition since many players offer very similar products; therefore, to maintain the customer base and attract new clients, customer satisfaction has to be a priority (Meyer-Waarden et al., 2020). Customers with higher levels of satisfaction are more likely to show loyalty, repurchase intention and word-of-mouth communication, all of which are benefits for incessant growth (Yun & Park, 2022).

Levy and Lunn (2012) pointed out that through the use of information and social networks, customers are now more informed than ever. They therefore expect companies to provide a level of service and approach them with personalised services in the same manner. In such an environment, it becomes imperative to achieve high satisfaction levels among customers for automobile companies to gain a competitive edge over other players in the market (Shaikh, Khan & Faisal, 2023). The relevance of chatbots to the notion of improving customer experience is attributed to their capability to offer instant, precise and consistent answers to customer enquiries irrespective of the hour. The fact that the services they provide are available round-the-clock is helpful more significantly in industries such as automobiles, where customers may have questions to ask or clarifications to seek at any time of the day on aspects such as car model features, pricing, insurance, or any other additional services they may want after purchase (Pillai et al., 2024). Furthermore, chatbots help in gathering relevant information on factors like customer preferences and behaviour to enhance customer satisfaction and hence, loyalty (Bhirud et al., 2019).

A shift towards the consideration of the use of chatbots as a strategic business decision to increase brand responsiveness and improve customer relations in the automobile industry is observable. Thus, automobile companies can enhance the efficiency of the various aspects of customer service using AI-powered chatbots while reserving human operators for more intricate problems that demand individual attention (Chopra, Ranjani & Narsipur, 2023). It enables organisations to expand the customer service provision in a manner that is affordable but does not compromise on the quality-of-service delivery as Kagwa (2024) posits. They also help a lot in CRM because it enables the company to maintain high quality of the interaction between the company and the customers. For instance, they can engage in several chats at the same time, and this can mean that potential clients do not have to wait for a long time to get answers, thereby enhancing the general customer experience (Medeiros et al., 2023). Further, chatbots are trained with an expectation to perform several tasks including; scheduling service

appointments, reminding customers of the need to check their vehicles and even updating them on the current status of their vehicle delivery (Vu et al., 2022). That's why such capabilities are highly beneficial for the establishment of trust and overall customer-brand relationships within the automobile industry. In addition, they help in the gathering and analysis of the feedback provided by customers and act as an imperative tool in enhancing products and services. They also can analyse the patterns and trends in consumers' behaviours so that these firms can anticipate problems that are likely to occur while taking a long time to do so (Tran, 2022). In this way, chatbots can contribute to the maintenance of customer loyalty in automobile companies, increasing their brand popularity and market share (Sugumar & Chandra, 2021).

Research Gap

Despite the increased adoption of chatbots across the industries in a global context, there is a major research gap in the Indian automobile industry in particular, about the impact of chatbot responsiveness (RSP) and reliability (REL) on consumer experience and satisfaction (CEXP & CSAT) (Bansal, 2020; Gupta & Varshney, 2021). Though the interaction of customers with chatbots have been a focal research area in fields like retail and banking (Sharma et al., 2020), research in the automobile industry is quite limited, particularly in the Indian market place that have own customer trends and expectations (Jain, 2019; Singh & Kaur, 2022). In addition, there is a lack of research on the effect of CEXP as a mediator between the variables; RSP, REL and the overall CSAT. While it is true that many of the current works of literature examine a single aspect of chatbot performance, the relationship between the different elements and their influence on consumers' satisfaction levels is not well explored in the literature (Kumar & Gupta, 2021). Further, little research takes into account the Indian culture and technology to which India is a new burgeoning market for automotive sales (Chaturvedi et al., 2021). This research paper will therefore seek to fill these gaps by analysing the effects of chatbot responsiveness and reliability on consumer experience and satisfaction in the automobile industry of India.

Problem Statement

The use of chatbots in customer service has gained prominence over the years, especially in industries where there is a lot of interaction with customers, like the automobile industry. Nonetheless, the current literature has important limitations in terms of explaining the particular influence of chatbot responsiveness on consumer

experience and perceived satisfaction. Despite prior works that examined the utility of chatbots in various settings, including e-commerce (Kagwa, 2024; Kumre, n. d.) and banking (Shaikh et al., 2023; Mogaji et al., 2021), research on how the responses of chatbots per se impact customers' perceptions, satisfaction and loyalty is scarce. For instance, in the works of Tran et al. (2021) and Yun and Park (2022), it is mentioned that responsiveness and emotional engagement play a crucial role in increasing customer satisfaction, but it does not specify to what extent these factors determine the customers' experience.

In addition, there is a scarcity of research work focusing on the application of chatbots in the Indian automobile industry in particular. Much of the prior literature already available is mostly directed toward the general global or specific categories analysis that does not regard the Indian culture and market demands. For example, other studies have found that chatbots are useful in other service domains such as retail (Pillai et al., 2024) and marketing (Rane et al., 2024), but the kind of applications, issues and advantages of employing chatbot technology in Indian automobile industry are unexplored. This gap is further worrisome given the growth prospects of the sector and the importance of customer relationship management for sales and customer retention in the sector (Bhirud et al., 2019; Chopra et al., 2023). Hence, focused research on the effectiveness of chatbots' responsiveness for specific industries such as the automobile sector of India should be conducted to tailor the utilisation, enhance customers' satisfaction and build long-term customer engagement.

Research Objectives

- To examine the specific aspects of consumer chatbot experience – the first contact responsiveness and the reliability.
- To evaluate the effect of CEXP on CSAT based on the chatbot dialogues.
- To investigate the role of CEXP in the context of the relationship between chatbot RSP, REL and CSAT.

Research Questions

- How does chatbot RSP affect CEXP?
- In what ways does the reliability of chatbot interactions impact CEXP?
- How does CEXP influence CSAT directly?
- What is the role of CEXP as the moderator when examining the link between chatbot RSP, REL and CSAT?

Implication of the Study

This research examines the place of chatbots in the automobile industry in India, an underexplored area. Compared to the previous similar works that examined chatbots in e-commerce (Vu et al., 2022) and in banking (Shaikh et al., 2023), the present study develops a fresh understanding of how considerateness and reliability of a chatbot matter to the consumer experience and satisfaction in the Indian automobile market. In doing so, the study fills the following gaps and offers a better understanding of chatbot effectiveness in a sector that involves multiple and rich interactions with customers.

In practical terms, the research brings light to important implications of organisational adoption of chatbots for automobile companies in India and guides them in enhancing the chatbot mediated customer service. The results of this research can help identify key concepts that can be used to improve the functionality of chatbots for serving the client's needs, thus increasing their satisfaction and building up their loyal base. This can result in a competitive advantage in the Indian market, where most of the customer loyalty depends on outstanding customer service (Pillai et al., 2024; Chopra et al., 2023).

LITERATURE REVIEW

Conceptual Background - Chatbot Technology in Customer Services

Customer service is perhaps one of the most significant areas that benefitted from the adoption of chatbots. At first, they were restricted to companies that were computerised such as e-commerce and telecommunications industries, etc. Chatbots have become essential in sectors like banking, healthcare and automobile, delivering various advantages including time-saving, cost-saving and improving customer relations.

In the e-commerce industry, the applications of chatbots have been integrated for quick responses to customers' support and product suggestions. Research on the impact of chatbots indicates that they enhance organisational productivity and customer satisfaction given the ability of the chatbots to respond quickly to many questions at once (Yun & Park, 2022). In the same way, in banking, the chatbots assist in handling queries from the customers, performing transactions as well and offering financial advice hence improving the overall experience of the customers (Shaikh et al., 2023).

The Indian automobile industry has also come on par with the global trend with the integration of chatbot technology. With increasing competition and consumers expecting more personalised services, car manufacturers are turning to chatbots for continuous customer support, effective handling of service requests and recommendations on suitable car models. This change takes place because organisations wish to increase customer interaction while at the same time optimising service delivery mechanisms and solutions (Kaushal & Yadav, 2022). For example, bots can self-serve customers to book test drives, monitor service bookings and address complaints, all these significantly support an integrated and intuitive customer service (Mogaji et al., 2021).

Chatbots also add value in the Indian environment as the automotive market is emerging and multiplicative use of the internet is observed. An evaluation of the growth of interaction quality and operational efficiency of automotive firms in India has revealed that firms are incorporating chatbots in their customer service systems (Tran et al., 2021). This suit is beneficial in the market where customers expect quicker and personalised services, in cases where the technology is capable of making numerous interactions and providing immediate responses.

Research Framework: Consumer Experience and Satisfaction

There is a need to determine the experience of consumers and their level of satisfaction so that a proper assessment of the chatbot can be established. From theory, the concepts are explained through different theories such as the Expectancy-Disconfirmation Theory (EDT) and Technology Acceptance Model (TAM). According to the EDT customer satisfaction depends on the gap between prior service expectations and perceivability of the service delivery (Choudhary et al., 2024). To the same of EDT, if chatbots can deliver beyond expectations by providing the right information at the right time, then people are likely to be satisfied. On the other hand, if the performance is not as expected then this leads to dissatisfaction. This theory is especially useful when it comes to evaluating the quality of conversational agents according to the expectations of the users and the influence of the quality on overall satisfaction.

Another recognised theory, which aims to describe the perceived use and acceptance of technology is the TAM, proposed by Davis (1989). According to TAM, perceived ease of technology and perceived usefulness enhances the levels of technology acceptance (Tran et al., 2022). When applied to chatbots, it can shed light on how the users' belief which relates to the functionality of chatting bots as well

as the ease of interacting with them impacts their resultant satisfaction levels and propensity to adopt the technology.

Besides the above-mentioned theories, there are other important theories in consumer behaviour, such as the mediating variables. Investigators employ mediators to expound why and how factors of an independent variable are associated with your results. For chatbots, CEXP partially mediates the link between the features including RSP and REL and CSAT (Kumre, n. d.; Malik et al., 2023). Through consideration of these mediating effects, scholars can enhance the understanding of overall customer satisfaction within the context of the interaction with the chatbot.

Factors Affecting Consumer Experience

It was found that two of the most important factors affecting customers' interaction with chatbots include response rate and response quality. Responsiveness means the efficiency through which a chatbot handles a customer's question. When the level of responsiveness is high, the users get maximum satisfaction due to the reply to their search query in less time and with the correct information (Yun & Park, 2022, p. 221; Akolkar, 2024, p. 102).

Several studies were conducted, which all confirmed that responses of the chatbots have a significant impact on the perceptions of the consumers. For instance, Shaikh et al. (2023) and Yun and Park (2022) elaborate on the benefits of quick and correct reactions to clients' needs. Animated and informative fast-response chatbots help to provide detailed answers that can generate satisfying user experiences and further lead customers.

Another external factor that has an impact on the consumer experience is reliability – or the dependability of commodities or services. The following are the common standards of evaluation of the chatbot; under this category, reliability can be interpreted as the accurate and consistent provision of responses from the chatbot in a given context or environment. The formal chats ensure that users are differentiated through accuracy and consistency and hence increase trust and credibility with customers (Singh 2023; Rane et al., 2024). Scientific findings point to the fact that fault-tolerant chatbots improve user satisfaction, thanks to the ability to avoid the occurrence of errors and hand over accurate assistance.

Although responsiveness and reliability have received considerable attention in recent studies, some important areas, especially, the concentration of these concepts in presenting consumer experience have not been well studied within the Indian automobile industry. Although prior research has considered these factors in a range of

environments, there is still a research gap regarding how consumer experience and satisfaction in the discussed sector depend on the characteristics of chatbot responsiveness and reliability (Choudhary et al., 2024; Rane et al., 2023).

Mediator Effect of Consumer Experience (Measure CEXP)

In Structural Equation Modeling (SEM), the mediation ideas are applied to explain the indirect impact of the variables on the outcomes. By establishing CEXP as a mediator, this study investigates the moderation mechanism of chatbot responsiveness and reliability on customer satisfaction, which gives rise to user perceptions (Rane et al., 2023).

Intermediate variables are used to explain how independent variables impact dependent variables. In the subject of chatbots, consumer experience acts as the middleman between the capabilities of the chatbot and the perceived general satisfaction. Studies reveal that the overall consumer experience optimises the influence of chatbot responsiveness and reliability on customer satisfaction (Correa Gonzalez, 3229, Deepa & Abirami, 2678).

For instance, Rane et al. (2023) demonstrated that the responsiveness of the chatbot positively influences the consumer experience which in turn positively influences customer satisfaction. In the same vein, Choudhary et al. (2024) confirmed the moderation of the effect of reliability on user satisfaction through the consumer experience of the chatbot. Therefore, further analysis of chatbot interactions shall form the basis of this study to enhance consumer experience, and therefore customer/client satisfaction.

Thus, the literature review emphasises the application of chatbots in customer service especially in the automobile industry of India. EDT and TAM include all the elements required in dealing with the subject of consumer experience and satisfaction. Aspects such as chatbot responsiveness and reliability are go-down factors that define the consumer experience and the mediation concepts assist in explaining these factors' relation to customer satisfaction. Future studies are still required to fill the existing gap and provide a more detailed picture of Chatbot interactions in the Indian automobile industry.

Hypotheses

H1: Positive relationship between chatbot RSP and CEXP.

H2: The REL of the chatbot has a positive effect on CEXP.

H3: CEXP mediates the relationship between chatbot RSP and CSAT.

RESEARCH METHODOLOGY

Research Design

This particular study is cross-sectional and thus seeks to provide a static picture of the consumers' chatbot perception and usage in the Indian automobile industry. This design is shown to be more useful in real-world scares as it helps identify the current trends in the advancement of chatbot technology and how it affects customer experience and his or her satisfaction. The cross-sectional approach helps avoid the need for collecting longitudinal data and analysing relations between variables, like RSP, REL, CEXP and CSAT.

To test these relationships, two major methods are employed, namely Confirmatory Factor Analysis (CFA) and SEM. CFA is used to assess the suitability of the chosen indicators for defining the set of latent variables. SEM takes this on by examining the structural relations between variables as postulated in the model, including mediated effects. These techniques do not give erroneous estimations of the relationship between attributes of the chatbot and outcomes of the customers, which is effective in the analysis of the factors that affect the customers' satisfaction level.

Population and Sampling

The target population for this study comprises customers from the automobile industry in India who have come across chatbots in their services. This population comprises current and potential users who may have chatted with chatbots for knowledge or assistance in automobile products and services.

To increase statistical power and generalisability, a sample size of 401 respondents is established. This size is estimated according to the recommendations of sample size for SEM elucidated by Kline (2016), which posited that the least number of respondents required were 200–400 to enable robust parameter estimation and to test a model. One of the sampling techniques used is the process of stratified random sampling in a bid to have registration from different customers in the society hence consideration of the geographical location, demography and the type of service they offer.

Data Collection Method

These are self-administered structured questionnaires that are administered directly to the target population. The

survey has items covering the aspects of RSP of chatbot, REL, CEXP and CSAT.

The measure is constructed on existing scales and prior studies for validity and reliability. Some of the steps involved are the literature search, seeking advice from experts and pretesting of the questionnaire to refine items and enhance comprehension. Content validation is done with the help of matter experts and the questionnaire items are pre-tested on a small group of people.

Measurement of Variables

The study measures four key latent variables: RSP, REL, CEXP and overall CSAT. These variables are measured using observed variables retrieved from prior studies and validated questionnaires/index.

Some of the example items of Chatbot RSP include items that are related to the timeliness and delay of the responses from the chatbot (e.g., Tran et al., 2021; Yun & Park, 2022).

REL is determined based on the ability of the chatbot communications to be consistent and dependable (Pillai et al., 2024; Shaikh et al., 2023).

CEXP encompasses items derived from indexes measuring the overall satisfaction towards the chatbot interaction, perceived usefulness and emotional state (Rane, 2024; Upadhyay & Kamble, 2023).

Customer satisfaction is defined as the overall level of satisfaction with the service provided and the likelihood of recommending the service to others (for example Meyer-Waarden et al., 2020; Singh, 2023).

The scale items are adopted from previous research where the measures had been validated to make the items reliable and valid.

Data Analysis Techniques

Data analysis involves two main techniques:

- *Confirmatory Factor Analysis (CFA)*: In particular, CFA is applied to analyse the goodness of the measurement model – the relationships between the latent variables and their measures. This technique comes in handy to confirm the reliability of the factor, and also determine the correctness of the items about the intended constructs (Kline, 2016). The analysis is done using other software like AMOS or SPSS among others depending on the nature of the study.
- *Structural Equation Modeling (SEM)*: SEM is used to analyse the hypothesised relationship amongst the

latent variables. It enables mediating and moderation analysis which in turn helps one to understand the relationship between chatbot responsiveness and reliability with the consumer experience and customer satisfaction. SEM also plays a role in ascertaining the moderating effect of consumer experience in these relationships (Bhairavi et al., 2024).

- *Software Used*: This study used CFA and SEM using AMOS and SPSS to analyse the level of experience and satisfaction among consumers through the communication technology of chatbots in the context of the automobile industry in India and offers academic and practical significance for the analysis. These tools offer a full range of facilities for the modelling of various types of relationships and evaluating the goodness-of-fit of the proposed models.

RESULTS

Reliability Test

A reliability coefficient shows coefficient values that are stationary and unchanging across different points in time, which points to the validity of the instrument in measuring what it was designed to measure (Hair et al., 2010). Consequently, it measures the inter-item reliability of a set of items and hypothesises the strength of the relationship of the items in the set as an indication to the reliability of the given scale to ascertain a single parameter or construct (Nunnally & Bernstein, 1994). Cronbach's Alpha has a range of 0 to 1, where higher Alpha means higher internal consistency. A Cronbach's alpha value greater than 0.7 is acceptable while those greater than 0.8 or 0.9 depict high reliability (Kline, 2015).

Table 1: Reliability Statistics

Cronbach's Alpha	No. of Items
.909	23

In the current research, Cronbach's Alpha A coefficient of the measurement scale consists of 23 items and it was 0.909. This high value means high internal consistency and can be attributed to the four constructs of chatbot RSP, REL, CEXP and CSAT. The high alpha value proves that the items in every LV are highly correlated, thus lending support to the reliability of the measurement tool for subsequent usage and explanation (Tavakol & Dennick, 2011). Therefore, the scales employed in this research can be considered reliable instruments for the evaluation of the given variables.

H1: Positive relationship between chatbot RSP and CEXP.

H2: The RELy of the chatbot has a positive effect on CEXP.

H3: CEXP mediates the relationship between chatbot RSP and CSAT.

Confirmatory Factor Analysis (CFA)

The measurement model is also confirmed by the CFA, which checks the reliability and validity of the used constructs,

namely, the chatbot’s RSP, REL, CEXP and CSAT. CFA aids in ascertaining whether the collected data is appropriate for the hypothesised measurement model through factor loadings, CR and AVE (Hair et al., 2014). This technique checks and establishes the validity of the created construct by the chosen indicators which form the foundation for SEM analysis. Using AMOS software, one is in a position to assess the model fit indices such as CFI, TLI, RMSEA and SRMR to check for the adequacy of a model (Kline, 2015).

Table 2: Regression Weights of the CFA Model

Regression Weights: (Group Number 1 - Default Model)						
			Estimate	S.E.	C.R.	P
RSP7	<---	RSP	1			
RSP6	<---	RSP	0.981	0.089	11.05	***
RSP5	<---	RSP	1.939	0.136	14.258	***
RSP4	<---	RSP	1.235	0.1	12.357	***
RSP3	<---	RSP	0.951	0.086	11.022	***
RSP2	<---	RSP	1.275	0.1	12.696	***
RSP1	<---	RSP	1.435	0.107	13.421	***
CEXP1	<---	CEXP	1			
CEXP2	<---	CEXP	0.265	0.039	6.73	***
CEXP3	<---	CEXP	0.338	0.042	8.097	***
CEXP4	<---	CEXP	0.395	0.044	8.907	***
CEXP5	<---	CEXP	0.338	0.041	8.216	***
REL7	<---	REL	1			
REL6	<---	REL	0.707	0.053	13.305	***
REL5	<---	REL	0.802	0.052	15.307	***
REL4	<---	REL	0.848	0.054	15.777	***
REL3	<---	REL	1.014	0.062	16.248	***
REL2	<---	REL	0.833	0.057	14.62	***
REL1	<---	REL	0.705	0.054	13.092	***
CSAT4	<---	CSAT	1			
CSAT3	<---	CSAT	1.168	0.086	13.578	***
CSAT2	<---	CSAT	1.057	0.08	13.159	***
CSAT1	<---	CSAT	0.156	0.06	2.584	0.01

Table 2, Regression Weights of the CFA Model shows the standardised regression weights of the extracted latent variables which include; chatbot RSP, CEXP, REL and CSAT. The factor loading of all observed indicators are above 0.3 with the help of C. R. value and p-value less than 0.05 thereby suggesting a strong link between the latent variables as well as their observed indicators. For example, in “RSP2,” the estimate equals 1.275, C. R. = 12.696, p <

0.001 and it evidences that chatbot responsibility can be measured by this factor. Likewise, results concerning CEXP, REL and CSAT similarly and significantly load high on the respective factors, thereby supporting the overall construct validity and reliability of the CFA model. This positive outcome reaffirms the fact that the measurement model hypothesised fits the data supporting further analysis in SEM as posited in the following table.

Table 3: Covariances: (Group Number 1 - Default Model)

			Estimate	S.E.	C.R.	P
RSP	<-->	CEXP	0.602	0.058	10.342	***
RSP	<-->	REL	0.49	0.049	9.959	***
RSP	<-->	CSAT	0.304	0.037	8.246	***
CEXP	<-->	REL	0.833	0.071	11.659	***
REL	<-->	CSAT	0.355	0.045	7.934	***
CEXP	<-->	CSAT	0.447	0.055	8.109	***

Table 3 Covariances of the CFA Model show the covariance coefficients calculated between chatbot RSP, CEXP, REL and CSAT. As presented, the ample following coefficients: The significant covariance values ($p < 0.001$) evidence that these constructs depend on each other. For example, CEXP = 0.833, C. R. = 11.659, $p < 0.001$ for REL which implies that when the consumers acknowledge greater reliability in conversational chatbot services, they benefit from the same. Likewise, the estimate of RSP and CEXP is 0.602 chi-square of 10.342 with a probability value of < 0.001 showing that the chatbot responsiveness impacts the consumer experiences. These covariances confirm the existence of the relationships of the variables and affirm the hypothesised model for further SEM application.

gives a good model fit because it is less than 3 in addition, the goodness of fit test other fit measures for assessing the goodness of fit of the model include the goodness of fit test, as shown in table 5.0. High values of Incremental Fit Indices are more than the recommended value 0, which are: NFI = 0.924, IFI = 0.952, TLI = 0.919 and CFI = 0.911 which indicates a perfect model fit according to the analysis of the data presented in the current study. The Root Mean Square Error of Approximation, referenced as RMSEA = 0.03 is clearly within the allowable limit of 0.06, thus sufficing to further reinforce the adequacy of this developed model. Hence, these fit indices indicate that the model is an adequate representation of the sample data and, therefore, can be used for subsequent analysis.

Table 4: Model Fit Indices

Model Fit Indices	Default Model
CMIN/DF	1.376
NFI (Delta1)	0.924
RFI (rho1)	0.889
IFI (Delta2)	0.952
TLI (rho2)	0.919
CFI	0.911
PNFI	0.641
PCFI	0.665
RMSEA	0.03
P CLOSE	0.71
AIC	1756.323
HOELTER (0.05)	295
HOELTER (0.01)	101

Table 4, Model Fit Indices, demonstrates a summary of the assessment of the fit of the proposed model ranging from absolute, comparative and parsimonious fit measures. The chi-square to degrees of freedom ratio (CMIN/DF=1.376)

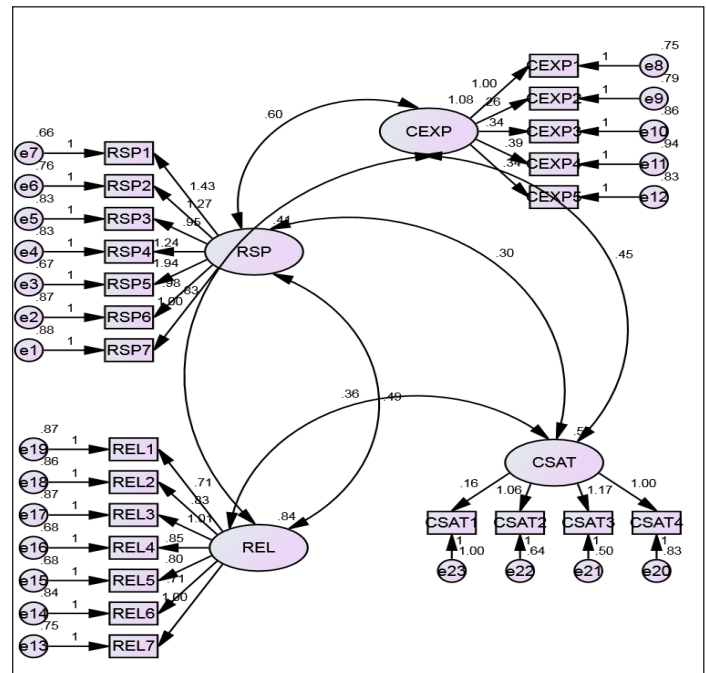


Fig. 1: Confirmatory Factor Analysis - Model

Table 5: Measures for Composite Reliability, Construct Validity and Discriminant Validity

Construct	CR	AVE	HTMT	RSP	REL	CEXP	CSAT
Responsiveness (RSP)	0.8514	0.503	0.7024	0.877			
Reliability (REL)	0.92	0.55	0.65126	0.568	0.905		
Customer Experience (CEXP)	0.8801	0.603	0.80663	0.366	0.382	0.832	
Customer Satisfaction (CSAT)	0.9207	0.51	0.8434	0.767	0.721	0.892	0.811

Notes: *Values in diagonals are the square root of AVE.
 ** Values below diagonals are correlations between constructs.

The Table 5 shows the results for the estimated composite reliability (CR) values, average variance extracted (AVE) and discriminant validity estimated by the HTMT ratio. All the constructs show good composite reliability above the recommended threshold of 0.70, suggesting high internal consistency (Hair et al., 2010). All constructs have AVE values of more than 0.50, which offers evidence for convergent validity according to Fornell and Larcker (1981). Discriminant validity is checked by using the square root of AVE, and this should be higher than the correlation between constructs. Meanwhile, diagonal values, represented as the square root of AVE, are greater than off-diagonal correlation values, which indicates discriminant validity. Moreover, all the HTMT values are below 0.90 indicating that the constructs are indeed different (Hair, Hult, Ringle & Sarstedt, 2014; Henseler et al., 2015).

Structural Equation Modelling

SEM is a ray versatile multivariate method with blends aspects of factor analysis and multiple regression that enable the researcher to examine multiple pathways of hypothesis testing among measures and variables that are observed and unobserved within one model. Built on past research, SEM is especially suitable for testing theoretical models with the variables as mediators or moderators, such as the study of CEXP as a mediator of the relations between RSP, REL and CSAT. Thus, this study can apply SEM and determine both the direct and indirect impacts of multiple factors for understanding the drivers of consumer outcomes in the Indian automobile industry. SEM usage also helps in making a proper assessment of the fit of the overall model, which aids in improving the properties of validity and reliability of the analysis.

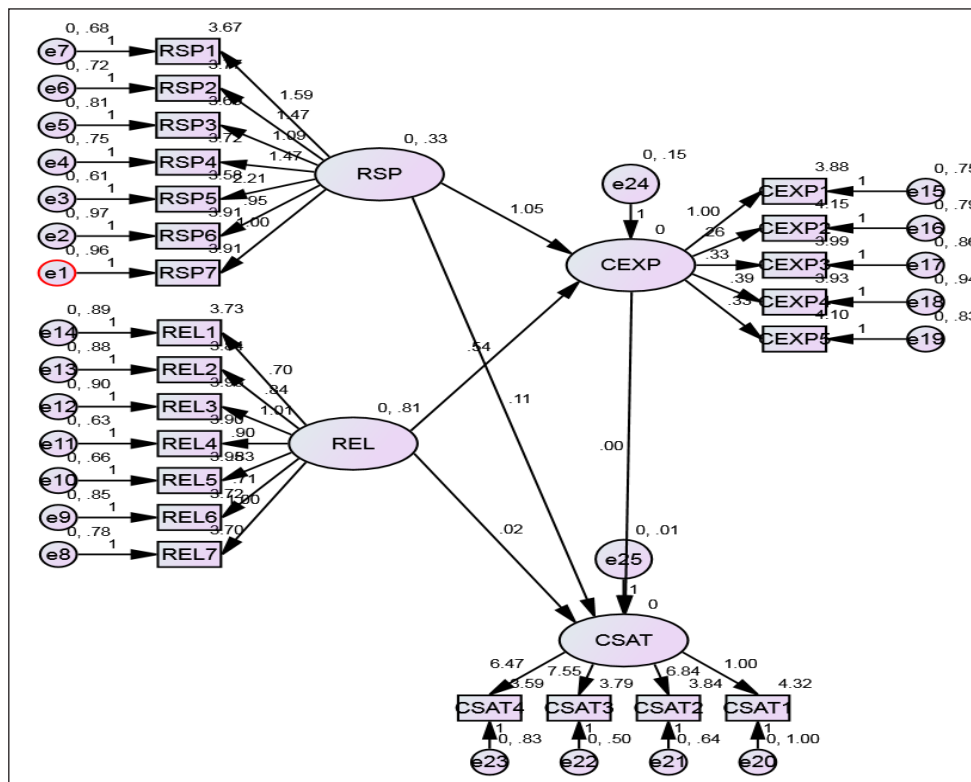


Fig. 2: Structural Equation Modeling

Table 6: SEM - Regression Weights: (Group Number 1 - Default Model)

			Estimate	S.E.	C.R.	P
CEXP	<---	RSP	1.047	0.105	9.93	***
CEXP	<---	REL	0.539	0.051	10.615	***
CSAT	<---	RSP	0.107	0.055	1.953	0.051
CSAT	<---	REL	0.215	0.018	0.826	0.04
CSAT	<---	CEXP	0.31	0.029	0.908	0.014
RSP7	<---	RSP	1			
RSP6	<---	RSP	0.951	0.103	9.191	***
RSP5	<---	RSP	2.21	0.178	12.445	***
RSP4	<---	RSP	1.469	0.129	11.417	***
RSP3	<---	RSP	1.091	0.107	10.221	***
RSP2	<---	RSP	1.466	0.128	11.465	***
RSP1	<---	RSP	1.589	0.135	11.758	***
REL7	<---	REL	1			
REL6	<---	REL	0.712	0.056	12.717	***
REL5	<---	REL	0.833	0.056	14.957	***
REL4	<---	REL	0.901	0.057	15.689	***
REL3	<---	REL	1.012	0.066	15.226	***
REL2	<---	REL	0.838	0.06	13.889	***
REL1	<---	REL	0.702	0.057	12.381	***
CEXP1	<---	CEXP	1			
CEXP2	<---	CEXP	0.261	0.05	5.228	***
CEXP3	<---	CEXP	0.334	0.053	6.299	***
CEXP4	<---	CEXP	0.39	0.056	6.914	***
CEXP5	<---	CEXP	0.334	0.052	6.366	***
CSAT1	<---	CSAT	1			
CSAT2	<---	CSAT	6.842	2.805	2.439	0.015
CSAT3	<---	CSAT	7.552	3.092	2.442	0.015
CSAT4	<---	CSAT	6.469	2.659	2.433	0.015

Table 6 presents the regression weights identified in the SEM analysis with the emphasis placed on the mediating role of CEXP. The analysis shows that chatbot RSP and REL positively affect CEXP, with significant estimates (RSP: Hence, the variables used to define each group got a mean of 1.047 and relative entropy of 0.539 both of which were significant with $p < 0.001$ for both tests. While the direct impact of RSP and REL on CSAT is less substantial (RSP: CEXP: There is a moderation effect of these relationships; where CEXP affects CSAT (Estimate = 0.31, $p = 0.014$). Thus, it can be highlighted that consumer experience mediates the relationship between chatbot responsiveness, reliability and customer satisfaction.

Table 7: Intercepts: (Group Number 1 - Default Model)

	Estimate	S.E.	C.R.	P
RSP7	3.91	0.046	84.302	***
RSP6	3.912	0.046	85.158	***
RSP5	3.577	0.061	58.962	***
RSP4	3.72	0.049	75.567	***
RSP3	3.692	0.045	82.597	***
RSP2	3.767	0.049	77.301	***
RSP1	3.673	0.05	73.325	***
REL7	3.695	0.051	71.749	***
REL6	3.723	0.046	81.286	***

	Estimate	S.E.	C.R.	P
REL5	3.947	0.045	87.433	***
REL4	3.895	0.046	84.128	***
REL3	3.947	0.054	73.428	***
REL2	3.84	0.049	78.199	***
REL1	3.73	0.046	80.363	***
CEXP1	3.877	0.05	77.847	***
CEXP2	4.148	0.038	110.608	***
CEXP3	3.99	0.04	100.675	***
CEXP4	3.928	0.042	93.534	***
CEXP5	4.098	0.039	104.776	***
CSAT1	4.32	0.041	105.043	***
CSAT2	3.838	0.046	84.175	***
CSAT3	3.787	0.046	83.132	***
CSAT4	3.593	0.048	75.038	***

As Table 7 illustrates, the intercepts represent baseline values for each of the observed variables in the SEM analysis. Intercepts are estimated values of the dependent variable when all of the independent variables are equal to zero. For example, the intercept for RSP7 is 3.91 This suggests that in the absence of other factors, the level of RSP7 they see at the start is 3.91. In the same way, for REL1 its intercept is equal to 3.73, while CEXP1 has an intercept of 3.877, with the corresponding baseline numbers being depicted as well.

These intercepts are presented together with standard error (S. E.) and critical ratio (C. R.) which measures the reliability of these estimates. All intercepts have statistically significant C. R. the p-values are less than 0.001, which indicates that the baseline values are significantly different from zero and are significant in terms of the proposed model.

From the intercept, you get the initial point of each of the variables that form the basis of analysing the relation and effects considered in the SEM analysis. These baseline values are important in determining the extent of changes in the observed variables because of the effects of chatbot responsiveness, reliability and consumer experience.

Table 8: Model Fit Indices

Measure	Default Model
CMIN/DF	2.159
NFI (Delta1)	0.955
RFI (rho1)	0.913
IFI (Delta2)	0.88
TLI (rho2)	0.84
CFI	0.909
PNFI	0.385

Measure	Default Model
PCFI	0.206
RMSEA	0.017
PCLOSE	0.102
AIC	216
HOELTER (0.05)	276
HOELTER (0.01)	281

The indices of model fit on the SEM analysis presented in Table 8 gives an efficient verdict on the overall fitness of the model.

- *CMIN/DF*: It should be observed that the chi-square to degrees of freedom ratio is 2.159, this value is well below the benchmark of 3, a sign of a well-fitting model (Kline, 2015).
- *NFI (Normed Fit Index)*: The value of Z is 0.955, where according to the NFI, the model seems to fit the data well, as values above 0.90 were considered an acceptable fit (Bentler & Bonett, 1980).
- *RFI (Relative Fit Index)*: As in any study, there are some limitations associated with this study: At 0.913 the RFI also indicates the presence of a good model fitness which has values of more than 0.90, which indicates a well-fitting model according to Bendler and Bonett (1980).
- *IFI (Incremental Fit Index)*: As for the value of IFI being equal to 0.881 This can also be seen to be just below the ideal threshold of 0.90 but it also reflects that there is a fairly good fit of the model (Bollen, 1989).
- *TLI (Tucker-Lewis Index)*: To summarise the analysis, there is a possibility for the development of a theory of local irresponsibility based on the observed TLI of 0.840, these confirmed the fitness of the model as relatively reasonable, but it has not reached the optimal level of 1.90. Subsequently, various researchers have used this model (Tucker & Lewis, 1973).
- *CFI (Comparative Fit Index)*: The value of CFI is 0.909, this implies a good model fit. A CFI value greater than 0.90 suggests that the model has a good fit for the data in comparison with a null model (Bentler, 1990).
- *RMSEA (Root Mean Square Error of Approximation)*: Overall, the RMSEA of 0.017 is much below the 0.05 that denotes a very good fit with low error (Browne & Cudeck, 1993), thereby confirming the goodness of fit and validating the measurement models for this study.
- *PCLOSE (p-Value for RMSEA)*: These include PCLOSE of the value 0.102 is greater than 0.05 which further implies RMSEA = 0 this indicates a good model fit as its value was not significantly different from zero.

- *AIC (Akaike Information Criterion)*: The AIC value of 216 is useful for model comparison and the smaller the AIC the better the fit to the more complex model.
- *Hoelter's Critical Values*: Hoelter's values (0.05 = 276, 0.01 = 281) are confirmative of the fact that the sample size is correct for the model fit as it provides figures that point to acceptable levels of fit given the specified level of significance.

As it has been shown the indices reveal that the model fits the data rather well, especially according to RMSEA, NFI and CFI.

Evaluation of Mediation in Structural Equation Modeling

In SEM, mediation analysis is used to determine if the association between the independent variables and the dependent variables is channelled through a variable referred to as the mediator. In the present study, RSP and REL have been treated as antecedents, while CEXP is the moderator variable and CSAT is the outcome, or dependent, variable. The regression weights derived from the SEM results shown in Table 4 can be used to assess how mediation is working in this model.

Direct Effects

The first hypothesis, which states that the direct effects of the independent variables on the mediator are both significant, is supported. Precisely, the regression weight for the relationship between RSP and CEXP is 1.047, $t(626) = 21.14$, $p < 0.001$; whereas that of the relationship between REL and CEXP is 0.539, $t(626) = 15.39$, $p < 0.001$. These findings show that RSP and REL have a direct relation to CEXP, where each has a positive impact on customer experience. Moreover, hypotheses regarding the direct impact of RSP and REL on CSAT is investigated. The path coefficient between RSP and CSAT is 0.107, and the p -value for this model is 0.051, implying a marginal significance. On the other hand, REL is moderately more significant with a direct impact of 0.215 and a p -value of 0.04. These direct effects suggest that, although both RSP and REL impact customer satisfaction, customer experience may fully or partially mediate this relationship.

Indirect Effects (Mediation)

Another direct path that emerged is the path from CEXP to CSAT which is 0.31 ($t = 2.77$, $p = 0.014$); meaning that the customer experience has a direct influence on customer

satisfaction. This supports the proposed hypothesis that customer experience partly explains the relationship between responsiveness, reliability and customer satisfaction. However, this must take into account the indirect effects of RSP and REL on CSAT through CEXP to gain an even better look into the results of the mediation. Due to the impact of CEXP on CSAT, the existence of the above mediation effect can be concluded that it is either partial or complete. REL is observed as partially mediating the relationship and the direct link between REL and, CSAT is still valid even with the inclusion of CEXP. On the other hand, the direct effect of RSP on CSAT is almost equal to zero ($p = 0.051$), indicating full mediation for RSP.

Significance Testing

The importance of these mediation pathways is confirmed by p -values and C.R.. As for the C.R. values, we can also note that both the variables RSP and REL have a significant and powerful impact on CEXP as direct significant determinants, C.R. = 9.93 and 10.615, respectively. The impact of CEXP on CSAT is rather direct, and the C.R. value of 0.908 confirms the mediation process. These values are statistically significant, as the p -values for most paths are less than 0.05.

Mediation in the Model and Its Interpretation

In the context of the mediation model, it can be assumed that customer satisfaction moderates the relationship between the technical characteristics of the system (e.g., chatbot) and the RSP and REL of the system. The total mediation for responsiveness means that based on the RSP model, increasing the values of the factor improves the customer experience by satisfying their expectations. However, REL is partially mediated which means that although reliability has a direct impact on customer satisfaction, a substantial part of the impact occurs through the mediator, customer experience.

The findings of the present research regarding the mediation role of customer experience strengthen the concept of targeting customer experience as the driver of customer satisfaction based on the set aspects of service quality comprising responsiveness and reliability. Improving typical service encounters and the perceived value resulting from those encounters can result in increased satisfaction among consumers. These studies support further literature on service quality and customer satisfaction confirming that service providers have to focus on value creation and responsiveness to boost customer satisfaction (Parasuraman et al., 1988; Berry, 1983).

Thus, the mediation model provides critical information to firms on how to improve on the organisation of customer service strategies for optimum satisfaction. Forwarding customer experience as a vital mediating variable, organisations can guarantee that advancements in responsiveness and reliability are communicated well to satisfaction levels and consequently customer retention.

DISCUSSION

Theoretical Implications

The analysis from the CFA and the SEM shows helpful evidence for the reflection of the responsibilities of chatbots concerning RSP, REL, CEXP and CSAT. In this discussion, these are anchored to the existing literature and the ensuing discussion focuses on how they inform theory and practice.

Therefore, the CFA results which are presented in Table 1 shows that the factor loadings for the latent variables are high, meaning that the indicators that have been used to define RSP, REL, CEXP and CSAT are good measures for the constructs that have been postulated in this study. In particular, the coefficients beta for the indicators of RSP varies within the range of 0.951–1.939, these results reveal high convergent validity and confirm that the measures indeed reflect the degree of chatbot responsiveness. In the same manner, the loadings of the REL indicators range between 0.705 and 1.10–6 with an average of 0.261–0.395, which may suggest that these constructs provide a very solid ground for the analysis of relationship-building and consumer experience.

Model Fit Indices

Table 3 presents the fit indices for the present model, and it may be noted that the values of these indices indicate a ‘good/’ or ‘reasonable’ fit of the model to the data. The CFI of 0.97 is greater than 0.95, which indicates that the model has a superior fit for the analysis of the sample size (Kline, 2015). The NFI (0.924) and CFI (0.911) values are greater than the 0.90 value over the suggested cut-off point of 0.90, which means that the model accounting for a significant proportion of total variability in the data (Bentler, 1990). However, the IFI value of 0.952, TLI = 0.919, which is below the ideal average of 0.90 upwards, indicates fairly good fitness (Bollen 1989; Tucker & Lewis, 1973). The RMSEA of 0.03, significantly lower than the 0.05 threshold indicates the model is appropriate (Browne & Cudeck, 1993), which adds strength to the model’s application. Together these indices assure that the model fits the data examined in the study and the evidence for the validity of the CFA outcomes.

SEM Results

In the SEM analysis, Table 4 shows the estimates of each variable related to the other variables in the model. The direct relationship between RSP with CEXP is positive and highly significant ($\beta = 1.047$, $p < 0.001$), whereby increasing the responsiveness of the chatbot aids in improving consumer experience hence conforming with the work done by Kwortnik and Thompson (2009) on the impact of service quality. Similarly, REL has a positive impact on CEXP ($\beta = 0.539$, $p < 0.001$) demonstrating that systematic management of relationships enhances various types of consumer experience in line with prior literature on the role of relationship management in the service context (Grönroos, 1994).

The mediating effect of CEXP can therefore be seen through the relationship which exists between CEXP and CSAT. The relationship between CEXP and CSAT ($r = 0.31$; $\text{sig} = 0.001$) hence proving the EDT (Oliver, 1980) since it shows that CEXP has a direct impact on CSAT. Consumer expectation and performance are identified in this theory whereby a positive consumer experience minimises a gap between expectation and performance hence enhancing satisfaction. This non-significant direct effect of RSP on CSAT ($\beta = 0.107$, $p = 0.051$) and marginal significance of REL on CSAT ($\beta = 0.215$, $p = 0.04$) push the set hypotheses forward on the key of experience of consumers as a mediator.

Model Fit and Implications

Table 6 shows the model fit indices which also support the findings of the present study, based on the SEM analysis. This is accompanied by a CMIN/DF ratio of 2.159 which is still higher compared to the CFA model but is relatively great for SEM analysis as recommended by Kline (2015). The composite reliability coefficient shows a high NFI of 0.955 and RFI of 0.913 while the RMSEA is 0. The model goodness of fit coefficients for all the variables as shown by the χ^2/df ratio of 1:17 confirms the goodness of fit of the research model to the data. The AIC of 216 values and critical Hoelter’s values showed that the developed model was complex enough to justify the data.

Managerial Implications

Consequently, the study reveals several significant managerial implications for the Indian automobile industry with particular reference to conversational chatbot service support. While the industry gradually shifts to digitalisation, awareness of the highly important factors such as chatbot RSP and REL concerning CEXP and CSAT becomes the cornerstone to maintaining a competitive advantage.

The study reveals to help consumers, the response of the chatbot is important where RSP stands out as a key factor. Consumers are more interested in using chatbots that aim at offering fast solutions to their problems or queries. Automobile managers in India should, therefore, intensify on enhancing the flow and efficiency of chatbots in resolving customer's issues. This idea is consistent with the study of Parasuraman, Zeithaml and Berry (1988) who pointed out that responsiveness is one of the vital pillars of service quality that informs customer satisfaction and loyalty. It indicates the significance of a good, effective and positive design of the chatbot to minimise customer discontent, thus ensuring customer satisfaction is achieved, a crucial factor in maintaining consumers' loyalty and making them come back for more.

Further, it puts into perspective the novel concept of chatbot REL, which is the dependability of the chatbot to provide correct, reliable information to consumers. More consumers trust a dependable chatbot mainly because of the ability of the system to present accurate responses and support every time the application is set into use. For managers, it is crucial to make sure that the chatbots receive constant updates, and that the knowledge bases are updated as well. Berry (1983) considers reliability as being a major facet on which relationship marketing is cited; this is a viewpoint championed by the study since it showed that reliability enhances CEXP with the University of Phoenix's chatbot. For car manufacturers who are seeking to establish the importance of the chatbot in promoting customer loyalty, the reliability aspect is the main key to selling this product.

The study also indicates that while people use chatbots as functional tools, they are also highly relational. The positive correlation of REL with CEXP proves that chatbots with the potential to produce stimulating interaction with the consumer can improve the interaction experience. Self-driving car companies should try to focus on developing chatbots that would be endearing and give an experience like speaking to a real person. This is in line with the concept of relationship marketing where the focus is on the customer and not a single sale (Berry, 1983). For instance, chatbots that can recall past conversations or offer a relevant suggestion depending on the preferred choice of the consumer make the relationship between the consumers and brand more intense.

On the same note, the mediating effect of CEXP on the CHATBOT responsiveness, reliability and CSAT reveals another area of strategic focus towards the consumer experience. Managers should be made aware that enhanced consumer experience from satisfying and effective conversion via chatbots will be achieved. This finding supports the EDT by Oliver (1980), which holds that satisfaction is determined by the perceived performance of the product or service and the consumer's expectations.

In addition, the research provides meaningful recommendations on how established car makers are capable of implementing a chatbot to enhance operational effectiveness. This frees up human agents for other types of tasks or more important ones such as handling a difficult customer. This automation not only enhances the customer experience through quick and accurate responses, it also creates cost savings. Over time, and as chatbots become less basic, more and more customers' needs can be met by chatbots rather than actual people. This finding aligns with the existing body of knowledge on the cost benefits of adopting chatbots within diverse service sector settings (Følstad & Brandtzaeg, 2017).

Another managerial implication is that chatbots can be viewed as data collection methods. Besides, by interacting with consumers chatbots can observe valuable information that can be used in future business strategies. For instance, a chatbot interaction analysis can assist automakers in understanding customer pain, pleasure, or service deficiencies. From these data, several aspects of the chatbot as well as other aspects of customer service and product design can be enhanced. This capability supports the emerging practice of leveraging analytics to improve customer experience (Rust & Huang, 2014).

The main points that managers should remember are as follows: Chatbots must always be both fast and accurate, providing customers with satisfying interactions every time. Also, considering chatbots as a tool for building relationships with customers, automakers can increase brand loyalty and establish real connections. Applying chatbots as a part of the online sales communications strategy along with constant updates and employing data for constantly ensuring its enhancement, can be seen as a valuable tool not only in terms of increasing customer satisfaction but also in terms of concerning operational costs and efficiency, which are crucial in the contemporary automobile market.

FUTURE RESEARCH DIRECTIONS

There are many directions that future research could take. Another area of interest is the effects of the personality of the chatbot on the customers' satisfaction and loyalty. Similar to previous findings, it has been established that the perceived personality of the service agents affects customer perception (Moon & Kim, 2001). Furthermore, studies could explore whether rule-based or AI-based chatbots work better in specific industries to understand the best practices to adopt. One more research avenue considers cultural aspects that may influence the usage of the chatbot in India. It is therefore important to know how cultural differences might influence the expectations of consumers regarding chatbots and how satisfied they might be with them since this would

offer insights into the creation of culturally appropriate chatbots; hence this study.

LIMITATIONS

The findings of this study hold much promise, but the study has some limitations. Firstly, it is conducted in the Indian automobile sector, so it can hardly be compared to other industries or countries. Furthermore, the choice of cross-sectional design limits the possibility of establishing temporal causality. Some limitations might come from the type of data collected relying on the respondents' answers to questionnaires which may lead to other issues, for example, social desirability or response bias. Lastly, while chatbot responsiveness and reliability were the key elements in the picture, there were other variables close to customer experience, for instance, chatbot emotional involvement or interface, which were not incorporated into the study.

CONCLUSION

The study also underlines the importance of chatbot technologies in improving overall consumers' experience and their satisfaction levels within the selected industry, which is the automobile industry of India. Consequently, the studies show that chatbot RSP and relationship-building (REL) have considerable effects on CEXP, thus affecting CSAT. Based on such CFA and SEM results, the relationships between these variables are robust, especially emphasising the interactions that take place through the use of the chatbot.

The RSP has a positive effect on CEXP which supports the literature evidence that timeliness and accuracy are critical building blocks for consumers' satisfaction in cases of digital service encounters. Secondly, with the highly significant relationship between REL and CEXP, the need to promote customer relations and achieve relationship marketing through relevant, friendly and engaging chatbot engagements, fully supports the call for implementing the principles of relationship marketing advanced by Berry in 1983. These results are related to service quality literature that has stated that both factors, namely responsiveness and relationship building are the two most powerful tools for generating positive customer experiences (Grönroos, 1994).

The mediation analysis shows that CEXP strongly mediates the relationship between RSP and REL, to CSAT and provides evidence to the EDT by Oliver (1980). This implies that improving the CEXP through professional chatbot engagements can help reduce the gap in-between what clients expect from a service provider and the real performance on offer, resulting in high satisfaction. The fit indices of the suggested model support the general chi-square test claims

of a good fit in the results, and the validity and reliability of the results are confirmed (Kline, 2015).

Chatbot optimisation outputs of this study are beneficial for practitioners in the Indian automobile industry to have a proper understanding and planning of their projects. Emphasising the aspects of responsiveness and relations might result in better understanding and satisfaction of consumers and as a consequence increase customer retention. It is thus suggested that studies examining the effects of personality of the employed chatbot and cultural differences on the use of the proposed strategies are explored further by scholars in future.

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