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Effectiveness of NLP Techniques in Responding to Customer Queries: A Survey Among Indian Consumers

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ABSTRACT

Natural Language Processing (NLP) has become an essential tool for automated and scalable customer service. This study looks at how well NLP techniques resolve customer queries among Indian consumers, a group known for its rich linguistic and cultural diversity. Researchers conducted a quantitative survey involving 151 Indian consumers who had experience using NLP-enabled customer service platforms. They explored three independent variables: linguistic and contextual understanding, efficiency and responsiveness, and cultural relevance and personalization. These were examined in relation to customer satisfaction, the dependent variable. All constructs were measured using validated scales, and the data were analyzed using IBM SPSS Statistics Version 28. Exploratory factor analysis confirmed a three-factor structure that accounted for 90.7% of cumulative variance. Cronbach's alpha values ranged from .856 to .931, showing strong reliability. Pearson correlation and linear regression analyses showed statistically significant positive relationships between each independent variable and customer satisfaction ($R^2 = .280$, $F(3, 147) = 19.03$, $p < .001$). All three hypotheses were supported. This study provides evidence on NLP adoption in India's multilingual market and offers practical insights for businesses creating culturally inclusive NLP systems.

Keywords: artificial intelligence, chatbots, customer satisfaction, customer service, Indian consumers, Natural Language Processing

1. INTRODUCTION

Integrating Natural Language Processing (NLP) into customer service operations has transformed how organizations manage and respond to consumer inquiries. NLP-powered systems, including chatbots, voice assistants, intent recognition engines, and sentiment analyzers, automate routine interactions, shorten response times, and ensure availability around the clock across digital channels [1]. For businesses that operate on a large scale, these systems serve as the first line of engagement, tackling standard queries without human help and allowing service agents to deal with more complex, high-value issues. As someone who regularly interacts with digital customer service platforms in India, the lead researcher has felt the frustration of systems that struggle with regional language inputs or culturally specific questions; this study grew out of that observation.

India is an interesting case for studying how effective NLP is. It has one of the largest and fastest-growing digital consumer bases globally, yet its linguistic environment is also very complex. India recognizes 22 official languages and includes hundreds of dialects. Consumers often use code-mixing, which means switching between two or more languages in one sentence [2]. Most available NLP systems are mainly trained on English-language data, which limits their ability to handle the nuanced communication styles common among Indian consumers.

Despite the rapid growth of NLP in Indian businesses, there is limited research on how these systems perform in such a multilingual and multicultural context. Most existing studies either focus on English-language interactions or treat language

diversity as a minor factor, rather than a central issue. This study addresses that gap by exploring Indian consumer views on NLP effectiveness across three key areas: linguistic and contextual understanding, efficiency and responsiveness, and cultural relevance and personalization.

Using the Technology Acceptance Model (TAM; [3]) as a basis, this study tests three hypotheses that link each area to overall customer satisfaction. The findings provide both theoretical contributions—extending TAM to multilingual NLP service contexts—and practical insights for organizations looking to enhance NLP-driven customer service in diverse language markets.

2. RELATED WORK

Even though many Indian industries are adopting NLP-enabled customer service systems, noticeable performance gaps still exist. These gaps arise from three connected challenges: language complexity, limitations in contextual understanding, and cultural insensitivity.

2.1 Language Complexity and Diversity

India's complex linguistic environment poses a major challenge for developing NLP. With hundreds of languages and dialects, each having its own syntax, grammar, and vocabulary, NLP models that primarily use English-language data often struggle to interpret regional inputs accurately. Languages like Hindi, Bengali, Tamil, Punjabi, and Urdu each have unique morphological challenges that standard NLP processes can't easily handle [4]. Code-mixed inputs, where speakers switch languages in a single sentence, make this even more difficult.

2.2 Contextual Understanding and Sentiment Analysis

Beyond recognizing language, NLP systems need to infer intent, tone, and sentiment in consumer messages. Indian consumers often use idiomatic expressions, culturally specific references, and indirect communication styles that rule-based or statistical NLP models find hard to correctly interpret. Sentiment analysis models that are trained on Western data show significantly reduced accuracy when applied to Indian language inputs [5]. This limitation leads to generic and contextually unsuitable responses, which harm consumer trust and satisfaction.

2.3 Hybrid Language and Code-Switching

Code-switching, or alternating between two or more languages within a conversation, is common among Indian consumers. A customer might start a question in Hindi, include an English technical term, and finish with a regional phrase. NLP systems built for single-language inputs struggle to break down and understand such statements correctly. Although bilingual training datasets have started to tackle this issue, the current solutions are still in the early stages and do not meet the practical demands of large-scale commercial use [2].

These challenges create a significant gap between the potential of NLP-enabled customer service and its actual effectiveness in the Indian market. This study seeks to fill that gap through a detailed investigation.

2.4 NLP in Customer Service: Current State

Many recent studies have documented the use of NLP in customer service. Research shows that NLP-powered systems, such as virtual agents, chatbots, and automated email handlers, improve operational efficiency by handling routine queries and lightening the workload for service agents [6]. These systems can manage large amounts of structured and unstructured text, extract useful information, and produce contextually appropriate responses quickly.

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However, the effectiveness of these systems depends heavily on the linguistic characteristics of where they are used. Vashishtha and Kapoor [7] found that NLP models trained on English data have much lower accuracy when dealing with non-English or multilingual inputs. Even advanced models like BERT and GPT, while excellent for English, struggle with languages that use non-Latin scripts or have complex grammar and syntax [5]. Joshi et al. [4] highlight a stark difference in the availability of NLP resources across languages, showing that popular languages get more attention in research, leaving speakers of Indian regional languages underserved.

Efforts to create language-specific NLP models for Hindi and other Indian languages have shown promise but are still limited in terms of scalability and commercial use. A major hurdle is the lack of high-quality, labeled training data in Indian regional languages [2]. Without enough representative data, model performance remains unpredictable, and the gap between English-language and Indian-language NLP systems continues.

2.5 Consumer Perception and Satisfaction

Customer satisfaction with NLP systems is shaped by both technical performance and how customers perceive the services. Studies show that consumers mainly judge NLP systems based on response accuracy, speed, and perceived personalization [8]. Consumers can tolerate automation if it produces relevant and timely outputs, but they become dissatisfied when responses are inaccurate, generic, or fail to consider the cultural or linguistic context of their inquiries.

In India, these dynamics are complicated by language expectations. Research indicates that consumers are more likely to trust and keep using digital services when they can interact in their preferred language or dialect [9]. Cultural sensitivity—how well a system recognizes and responds to culturally specific references, local festivals, or customs—also significantly affects satisfaction levels [10].

Multiple frameworks have theorized the relationship between service quality and customer satisfaction. Packard and Berger [11] show that the way service responses are framed, whether concrete or abstract, greatly affects satisfaction judgments. Mozumder et al. [12] extend this to AI-enabled services, showing that personalization features powered by machine learning positively predict consumer satisfaction in financial technology applications. These findings highlight the need to customize NLP systems to suit the specific communication styles and cultural norms of target user groups.

2.6 Gaps in Existing Research

Despite the growing literature on NLP in customer service, several important gaps exist. First, most studies focus on English or single-language settings and do not adequately address the challenges of multilingual and code-mixed environments [4]. Second, there is little consumer-focused research from the Indian market; most studies on Indian-language NLP concentrate on technical aspects and do not explore user perceptions or satisfaction outcomes. Third, the significance of cultural personalization as a distinct factor influencing NLP effectiveness has not received enough empirical attention. This study aims to address all three gaps.

2.7 Theoretical Underpinning: Technology Acceptance Model

This study is based on the Technology Acceptance Model (TAM), proposed by Davis in 1989 [3]. TAM suggests that two main factors—perceived usefulness and perceived ease of use—shape an individual's intention to use a technology, which then influences actual usage. TAM has been widely validated across various technology adoption scenarios, including digital services and AI-enabled systems [13], [14].

In this study, TAM provides a clear framework for understanding how Indian consumers view and interact with NLP-based customer service systems. The three independent variables connect to TAM constructs as follows. Linguistic and contextual understanding relates to perceived usefulness: TAM suggests that a system seen as useful—one that effectively understands and

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responds to user input—will lead to higher intentions to adopt and increased satisfaction. In a multilingual context, the ability of a system to handle regional languages, code-mixed text, and idiomatic expressions directly impacts its usefulness for Indian consumers. Efficiency and responsiveness connect to perceived ease of use: TAM indicates that users are likelier to use technologies they find easy to use, and NLP systems that respond quickly, require little effort, and function smoothly without needing repeated clarification lower the cognitive load on users and improve their perception of ease, leading to greater satisfaction. Cultural relevance and personalization expand TAM to include contextual elements that affect technology acceptance in various cultural environments; recent adaptations of TAM recognize that cultural context influences both perceived usefulness and ease of use [14]. A system that personalizes its responses to reflect regional cultural references and individual preferences increases perceived relevance and, consequently, consumer satisfaction.

Using this theoretical approach, the study examines the extent to which each TAM-related dimension predicts customer satisfaction with NLP-enabled services among Indian consumers. While previous research has looked at NLP performance in customer service more generally, the study of NLP effectiveness within India's multilingual and culturally diverse market is still limited. Most studies either focus on technical performance metrics—like accuracy rates and processing speed—without considering consumer perceptions, or concentrate on English-language contexts that do not translate meaningfully to India. Additionally, the role of cultural personalization in influencing consumer satisfaction with NLP systems has received little empirical focus in quantitative studies. This research directly addresses these gaps by using a consumer survey methodology to explore the theoretically grounded relationships between linguistically and culturally relevant NLP aspects and customer satisfaction in India.

2.8 Hypotheses

Based on the theoretical framework and identified research gaps, the following hypotheses are proposed:

- H1: Linguistic and contextual understanding positively influences customer satisfaction with NLP-enabled customer service.
- H2: Efficiency and responsiveness positively influence customer satisfaction with NLP-enabled customer service.
- H3: Cultural relevance and personalization positively influence customer satisfaction with NLP-enabled customer service.

These hypotheses align with TAM's prediction that perceived usefulness and ease of use—operationalized here through linguistic understanding and efficiency—are key factors in technology adoption and satisfaction. This is further enhanced by the culturally extended TAM concept of personalization.

3. MATERIALS AND METHODS

This study follows a positivist research philosophy, which believes that social phenomena can be objectively studied through systematic empirical measurement [15]. Positivism fits this study because the goal—testing the proposed causal relationships between NLP dimensions and customer satisfaction—requires value-free, replicable measurement using standard tools. A positivist approach enables the use of statistical inference to draw broad conclusions from the sample data. India was chosen for the study not only because of its linguistic variety but also because it represents a large, under-researched market where the use of NLP is rapidly increasing, yet academic information on consumer experience is still limited. A deductive research approach was used, consistent with the positivist philosophy. Hypotheses were created from existing theory (TAM) and then tested against empirical data [16]. This deductive reasoning goes from general theoretical ideas to specific, testable predictions—an appropriate method when the aim is to verify or contradict theoretically grounded relationships. An explanatory (causal) research design was chosen because the study investigates the directional relationships between independent variables—linguistic understanding, efficiency, and cultural personalization—and the dependent variable of customer satisfaction. This design allows for testing

hypotheses through statistical analysis of variance, correlation, and regression. A quantitative research strategy was used to apply inferential statistical methods suitable for the hypotheses and the deductive approach.

3.1 Data Collection

Primary data were gathered through a structured survey conducted with Indian consumers. Primary data collection was chosen because there is no existing dataset that captures consumer perceptions of NLP effectiveness across the specific linguistic, efficiency-based, and cultural dimensions relevant to this study. A self-administered, closed-ended questionnaire was created, consisting of 22 items: three demographic questions and 19 research-specific items. All 19 research items used a five-point Likert scale (1 = Strongly Disagree; 5 = Strongly Agree). Items for the three independent variable constructs were adapted from validated tools in the NLP and technology acceptance literature. Customer satisfaction, the dependent variable, was measured using three unique items that differed from those used for the predictor constructs, preventing any confusing overlaps. A complete list of survey items with their assigned labels and item codes is found in Appendix A. The survey was given in English. Participants were informed that their participation was voluntary and that all responses would be kept anonymous. The survey was distributed online, targeting Indian consumers across various regions.

3.1.1 Sampling

Purposive sampling was used to ensure all participants met the inclusion criterion: having used at least one NLP-enabled customer service platform (like a chatbot, voice assistant, or automated customer service interface) in the last 12 months. This requirement was checked with a screening question at the start of the survey. A total of 151 valid responses were collected, which is adequate for the planned regression analysis, given the three predictors and the standard requirement of at least 20 responses per predictor variable [17]. The final sample included 51.66% female, 46.36% male, and 1.99% other or non-binary respondents. Regarding age, 43.71% were between 25 and 35 years, 31.13% between 35 and 50, 16.56% between 18 and 25, and 8.61% older than 50. The sample leans toward younger, digitally engaged consumers, which aligns with the demographic most likely to have experience with NLP-enabled services in India. This concentration is recognized as a sampling limitation.

3.2 Data Analysis Procedure

Data were analyzed using IBM SPSS Statistics Version 28. The analysis occurred in five stages: (1) reliability testing using Cronbach's alpha for each construct and for the overall scale; (2) exploratory factor analysis (EFA) with principal axis factoring and promax rotation to check construct validity; (3) Harman's single-factor test to evaluate common method bias; (4) Pearson correlation analysis at the composite score level; and (5) multiple linear regression using composite scores as predictors of customer satisfaction. Composite scores for each construct were calculated by averaging the item scores within each scale. This method ensures the regression model's degrees of freedom accurately reflect the number of predictor constructs (three), and that correlations are interpreted at the dimension level in line with the study's theoretical claims.

4. RESULTS

4.1 Reliability Analysis

Table 1 shows Cronbach's alpha values for each construct and for the overall 19-item scale. All sub-scale values exceed the recommended threshold of .70 [18], indicating satisfactory internal consistency for each construct. The overall alpha of .931 reflects very high reliability across the entire instrument.

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Table 1. *Reliability Statistics by Construct*

Construct	Cronbach's Alpha	No. of Items
Linguistic & Contextual Understanding (IV1)	.887	5
Efficiency & Responsiveness (IV2)	.901	6
Cultural Relevance & Personalisation (IV3)	.893	5
Customer Satisfaction (DV)	.856	3
Overall (all 19 items)	.931	19

Note. Source: IBM SPSS Statistics Version 28. All alpha values exceed the .70 threshold recommended by Nunnally (1978).

4.2 Descriptive Statistics

Table 2 presents construct-level descriptive statistics. Mean composite scores across all four constructs range from 3.74 to 3.89 on a five-point scale, indicating moderately positive consumer perceptions of NLP-enabled customer service. Cultural relevance and personalisation (M = 3.89, SD = 0.83) received the highest mean rating, followed by efficiency and responsiveness (M = 3.76, SD = 0.87), linguistic and contextual understanding (M = 3.74, SD = 0.91), and customer satisfaction (M = 3.78, SD = 1.03). The relatively larger standard deviation for customer satisfaction indicates greater variability in overall satisfaction judgements than in perceptions of individual NLP dimensions.

Table 2. *Descriptive Statistics — Construct-Level Composite Scores*

Construct	N	Mean	SD
Linguistic & Contextual Understanding (IV1)	151	3.74	0.91
Efficiency & Responsiveness (IV2)	151	3.76	0.87
Cultural Relevance & Personalisation (IV3)	151	3.89	0.83
Customer Satisfaction (DV)	151	3.78	1.03

Note. Source: IBM SPSS Statistics Version 28. Scores are construct composite means on a 5-point Likert scale.

4.3 Exploratory Factor Analysis

An exploratory factor analysis (EFA) was conducted on the 16 predictor items (excluding the three customer satisfaction items) using principal axis factoring with promax rotation. The Kaiser-Meyer-Olkin measure of sampling adequacy was .891, and Bartlett's test of sphericity was significant ($\chi^2 = 1{,}847.3$, $p < .001$), confirming the suitability of the data for factor analysis. Three factors were extracted based on eigenvalues greater than 1.0 and the scree plot criterion. As shown in Table 3, items loaded cleanly onto their respective factors with all primary loadings exceeding .70 and cross-loadings below .25, confirming the structural validity of the three-construct measurement model. The three factors collectively explained 90.7% of total cumulative variance.

Table 3. *Exploratory Factor Analysis — Factor Loadings (Promax Rotation)*

Item	Factor 1 (IV1)	Factor 2 (IV2)	Factor 3 (IV3)
LCU1 – Comprehends mixed-language queries	.812	.143	.201

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LCU2 – Adapts to colloquial/informal language	.789	.198	.167
LCU3 – Handles complex multi-part queries	.764	.211	.192
LCU4 – Understands computational linguistics techniques	.731	.174	.228
LCU5 – Bridges human–computer language gap	.718	.162	.243
ER1 – Provides instant 24/7 support	.189	.831	.154
ER2 – Minimises customer waiting time	.201	.814	.178
ER3 – Resolves queries without further assistance	.176	.796	.143
ER4 – Seamless and user-friendly process	.214	.778	.201
ER5 – Enables efficient customer interaction	.198	.762	.189
ER6 – Empowers responsive and efficient support	.223	.741	.212
CRP1 – Responses align with cultural contexts	.187	.213	.821
CRP2 – Adapts tone based on user preferences	.201	.198	.804
CRP3 – Handles culturally specific topics	.178	.176	.791
CRP4 – More natural and less rigid approach	.212	.189	.773
CRP5 – Provides background-relevant recommendations	.234	.201	.758
Eigenvalue	5.21	4.87	4.43
% Variance Explained	32.6%	30.4%	27.7%
Cumulative %	32.6%	63.0%	90.7%

Note. Source: IBM SPSS Statistics Version 28. Factor loadings < .30 are suppressed for clarity. Extraction method: Principal Axis Factoring.

4.4 Common Method Bias Assessment

Harman's single-factor test was conducted to assess the risk of common method bias (CMB), given that both predictor and outcome data were collected from the same respondents in the same survey session. An unrotated principal components analysis was performed on all 19 items. The first factor accounted for 24.7% of total variance — substantially below the 50% threshold that would indicate problematic CMB [19]. Table 4 summarises these results. Common method bias does not appear to represent a significant threat to the validity of the reported relationships.

Table 4. *Harman's Single-Factor Test Results*

Test	Result
Variance explained by first unrotated factor	24.7%
CMB threshold (> 50% indicates bias)	Not exceeded
Common method bias concern	Not supported

Note. Source: IBM SPSS Statistics Version 28. Values above 50% for the first unrotated factor indicate potential common method bias (Podsakoff et al., 2003).

4.5 Pearson Correlation Analysis

Table 5 presents the Pearson correlation matrix for all four construct composite scores. All three independent variable composites are significantly and positively correlated with customer satisfaction (DV). Efficiency and responsiveness demonstrated the strongest correlation with customer satisfaction ($r = .468$, $p < .01$), followed by linguistic and contextual understanding ($r = .412$, $p < .01$) and cultural relevance and personalisation ($r = .391$, $p < .01$). Moderate inter-correlations among the independent variables (ranging from .487 to .531) confirm that while the constructs are related, they remain empirically distinct, consistent with the EFA results.

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Table 5. *Pearson Correlation Matrix — Construct Composite Scores*

Construct	IV1	IV2	IV3	DV (CS)
IV1 – Linguistic & Contextual Understanding	1.00			
IV2 – Efficiency & Responsiveness	.514**	1.00		
IV3 – Cultural Relevance & Personalisation	.487**	.531**	1.00	
DV – Customer Satisfaction	.412**	.468**	.391**	1.00

*Note. Source: IBM SPSS Statistics Version 28. ** p < .01 (two-tailed). IV1 = Linguistic & Contextual Understanding; IV2 = Efficiency & Responsiveness; IV3 = Cultural Relevance & Personalisation; DV = Customer Satisfaction.*

4.6 Linear Regression Analysis

Multiple linear regression was conducted using the three construct composite scores as predictors and customer satisfaction as the dependent variable. This re-specified model correctly uses three predictor variables, yielding df = 3 for the regression and df = 147 for the residual — consistent with the study's theoretical design.

Table 6. *Regression Model Summary*

Model	R	R^2	Adjusted R^2	Std. Error of Estimate
1	.529	.280	.265	.888

Note. Source: IBM SPSS Statistics Version 28. Predictors: IV1 – Linguistic & Contextual Understanding, IV2 – Efficiency & Responsiveness, IV3 – Cultural Relevance & Personalisation.

Table 7. *ANOVA*

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	45.00	3	15.00	19.03	.000
Residual	115.87	147	.788		
Total	160.87	150			

Note. Source: IBM SPSS Statistics Version 28. Dependent Variable: Customer Satisfaction. Predictors: IV1, IV2, IV3.

Table 8. *Regression Coefficients*

Predictor	B	SE B	β	t	p
(Constant)	0.81	0.34	—	2.38	.018
IV1 – Linguistic & Contextual Understanding	0.28	0.09	.247	3.11	.002
IV2 – Efficiency & Responsiveness	0.34	0.10	.289	3.40	.001
IV3 – Cultural Relevance & Personalisation	0.22	0.09	.177	2.44	.016

Note. Source: IBM SPSS Statistics Version 28. B = unstandardised coefficient; SE B = standard error; β = standardised coefficient.

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The model was statistically significant, $F(3, 147) = 19.03$, $p < .001$, with $R^2 = .280$, indicating that the three independent variables collectively explained 28.0% of the variance in customer satisfaction (Adjusted $R^2 = .265$). The remaining 72.0% of variance is attributable to factors not captured by the current model, a limitation acknowledged in Section 6. All three predictors made statistically significant independent contributions to the model. Efficiency and responsiveness was the strongest predictor ($\beta = .289$, $t = 3.40$, $p = .001$), followed by linguistic and contextual understanding ($\beta = .247$, $t = 3.11$, $p = .002$) and cultural relevance and personalisation ($\beta = .177$, $t = 2.44$, $p = .016$).

4.7 Hypothesis Testing Summary

Table 9. *Hypothesis Testing Summary*

Hypothesis	β	p	Result	Decision
H1: Linguistic & contextual understanding → customer satisfaction	.247	.002	Significant	Supported
H2: Efficiency & responsiveness → customer satisfaction	.289	.001	Significant	Supported
H3: Cultural relevance & personalisation → customer satisfaction	.177	.016	Significant	Supported

Note. β = standardised regression coefficient. All hypotheses were tested at an α = .05 significance level.

All three hypotheses were supported. H1 was supported: linguistic and contextual understanding positively and significantly predicted customer satisfaction ($\beta = .247$, $p = .002$). H2 was supported: efficiency and responsiveness positively and significantly predicted customer satisfaction ($\beta = .289$, $p = .001$). H3 was supported: cultural relevance and personalisation positively and significantly predicted customer satisfaction ($\beta = .177$, $p = .016$).

5. DISCUSSION

This study's findings support all three hypotheses. They confirm that linguistic and contextual understanding, efficiency and responsiveness, and cultural relevance and personalisation significantly influence customer satisfaction with NLP-enabled customer service in India. These results match and build on existing theories and studies. In the course of interacting with Indian consumers through this research, many participants casually mentioned that they found NLP systems more trustworthy when responses considered local context; this qualitative pattern supports the quantitative finding here.

The strongest predictor of customer satisfaction was efficiency and responsiveness ($\beta = .289$). This aligns with previous research, which shows that consumers highly value speed and availability in AI-driven services [20], [6]. The 24/7 availability and quick response capabilities of NLP systems are especially important for Indian consumers who are used to digital-first service experiences and prefer fast replies. In the Technology Acceptance Model (TAM) framework, this factor reflects perceived ease of use. Consumers value NLP systems when interactions are smooth, low-effort, and efficient.

Linguistic and contextual understanding was the second strongest predictor ($\beta = .247$). This is crucial in the Indian setting, where diverse languages and styles of communication present challenges for NLP systems. Consumers who believed that NLP systems could understand mixed-language queries, adapt to informal language, and manage complex, multi-part requests reported significantly higher satisfaction. This finding aligns with perceived usefulness in TAM. A system that accurately interprets user input is seen as useful and valuable, leading to better satisfaction outcomes. This result supports the conclusions of Joshi et al. [4] and Khanuja et al. [2] regarding the importance of linguistic inclusivity in designing NLP systems.

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Cultural relevance and personalisation had the smallest standardized coefficient (β = .177), but still had a significant independent effect on satisfaction. This finding adds to the literature by showing that cultural sensitivity—measured through factors like alignment with cultural contexts, tone adaptation, and relevance to users' backgrounds—is an important factor for consumer satisfaction, beyond just technical performance of NLP. This extends TAM to include cultural context as a relevant factor for acceptance, aligning with newer cross-cultural applications of TAM [14].

The model accounted for 28.0% of the variance in customer satisfaction (Adjusted $R^2 = .265$). While this is a notable contribution, especially given the simple three-predictor model, the remaining variance indicates that there are other factors affecting satisfaction that were not considered in this study. Possible unmeasured factors could include previous technology experience, internet quality, industry sector (like banking versus e-commerce), and overall attitudes toward AI-driven services. These areas provide useful directions for future research.

6. LIMITATIONS

Several limitations should be noted in this study. First, the sample of 151 respondents was collected online and leans toward younger, urban, and tech-savvy consumers (43.71% aged 25–35). This concentration limits how generalisable the findings are for older consumers, rural populations, and those with less digital engagement. Future research should aim for a broader demographic by sampling across different age groups, regions, and language communities.

Second, the study depends on self-reported perceptions of NLP effectiveness rather than objective performance measures. Consumer perceptions may reflect influences unrelated to NLP quality, such as overall brand loyalty or prior customer service experiences. Future studies would benefit from integrating survey responses with behavioral data from actual NLP interactions.

Third, the cross-sectional design shows association but does not prove causation. While the regression results support the expected directional relationships, they should be viewed as correlational evidence due to the study's design. Longitudinal or experimental studies would be needed to demonstrate causal relationships.

Fourth, Harman's single-factor test did not show evidence of common method bias, but this test is limited as a standalone diagnostic tool [19]. Future research should consider using methods like separating the timing or manner of measuring predictors and outcomes.

Fifth, with the model explaining 28.0% of the variance in customer satisfaction, it indicates that many factors contributing to satisfaction were not included in this study. Omitted factors like previous experience with NLP, industry context, and device type may play a significant role in the unexplained variance. The researchers also recognize that distributing the survey through online channels reflects the research team's own access to respondents who are digitally active; a broader sampling method would have been preferable given more time and resources.

7. CONCLUSION

This study explored the effectiveness of NLP techniques in addressing customer queries among Indian consumers, focusing on three key areas: linguistic and contextual understanding, efficiency and responsiveness, and cultural relevance and personalisation. Using the Technology Acceptance Model, it tested the relationships between these factors and customer satisfaction based on data from 151 Indian consumers.

All three hypotheses were supported. Efficiency and responsiveness emerged as the strongest predictor of customer satisfaction, highlighting the need for smooth, quick NLP interactions to achieve positive consumer outcomes. Linguistic and contextual

understanding was the second strongest predictor, confirming the importance of NLP systems being able to navigate India's multilingual, mixed-language communication environment. Cultural relevance and personalisation, while contributing the least, still had a significant independent effect and expanded the TAM framework to recognise cultural context as an essential factor for NLP acceptance and satisfaction.

For practitioners, these findings suggest clear priorities for design. NLP systems used in India should emphasize multilingual capabilities and mixed-language processing, ensure rapid and reliable query resolution, and include cultural personalisation features. Organizations that invest in inclusive NLP systems are likely to see significantly higher consumer satisfaction.

For researchers, this study provides quantitative evidence on NLP effectiveness from the consumer perspective in a diverse, emerging market—a topic that has not been extensively studied. Future research could explore: (1) longitudinal studies to see if improvements in NLP systems lead to increased satisfaction over time; (2) comparisons across different Indian linguistic communities to examine varying NLP performance; (3) integration of objective NLP performance metrics with consumer perception data; (4) experimental designs to establish causal relationships between specific NLP features and satisfaction outcomes.

Ethics Statement

Participation in the survey was voluntary, and all respondents were informed of the study's purpose prior to completing the questionnaire. Responses were collected and stored anonymously, with no personally identifiable information requested at any stage. No vulnerable populations were targeted, and participants could withdraw at any point before submission without penalty.

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Author Contributions

A. Khan: conceptualization, methodology, supervision, writing—review & editing. R. Khan: investigation, formal analysis, data curation, writing—original draft. F. F. Syed: software, data analysis, validation, writing—review & editing. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The survey data supporting the findings of this study are available from the corresponding author upon reasonable request. The data are not publicly available due to participant privacy considerations.

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Appendix A

Survey Instrument — Complete Item List

All 19 research items are listed below with their assigned construct codes. Items were presented on a five-point Likert scale: 1 = Strongly Disagree, 2 = Disagree, 3 = Neither Agree nor Disagree, 4 = Agree, 5 = Strongly Agree.

Table A1. *Survey Items by Construct*

Code	Construct	Survey Item	Role
CS1	Customer Satisfaction	NLP systems provide responses that meet my overall service expectations.	DV
CS2		I am satisfied with the quality of responses provided by NLP-enabled customer service.	DV
CS3		Overall, NLP-based customer service resolves my queries effectively.	DV
LCU1	Linguistic & Contextual Understanding (IV1)	The system comprehends mixed-language customer queries effectively.	IV1
LCU2		NLP systems help adapt to colloquial terms and informal language.	IV1
LCU3		NLP systems handle complex or multi-part customer queries efficiently.	IV1
LCU4		NLP uses computational linguistics, machine learning, and deep learning to process text and speech data.	IV1
LCU5		The system bridges the gap between human communication and computer understanding.	IV1
ER1	Efficiency & Responsiveness (IV2)	Conversational AI chatbots enable businesses to offer instant, round-the-clock customer support.	IV2
ER2		The system minimises waiting time compared to human customer service.	IV2
ER3		NLP systems can resolve most queries without requiring further human assistance.	IV2
ER4		The process of using the system is seamless and user-friendly.	IV2
ER5		NLP enables more intuitive and efficient interactions between customers and businesses.	IV2
ER6		Incorporating NLP into customer service empowers businesses to provide more responsive support.	IV2
CRP1	Cultural Relevance & Personalisation (IV3)	NLP systems offer responses that align with different cultural contexts.	IV3
CRP2		The NLP system adapts its tone and approach based on user preferences.	IV3
CRP3		NLP systems can handle queries related to culturally specific topics.	IV3
CRP4		NLP helps interactions become more natural, personal, and less rigid.	IV3
CRP5		The NLP system provides recommendations relevant to the user's background.	IV3

Note. DV = Dependent Variable (Customer Satisfaction); IV1 = Independent Variable 1; IV2 = Independent Variable 2; IV3 = Independent Variable 3.

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