

Weighting Customer Perceptions of AI Chatbots in E-Commerce: An AHP-Based Evaluation Framework

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Publication Date: 2026/10/01

Abstract: This study applies the Analytic Hierarchy Process to evaluate e-commerce chatbots across five customer-centered criteria: responsiveness, personalization, reliability, ease of use, and service quality. Chatbot services associated with Amazon, Myntra, Meesho, Flipkart, and AJIO are compared using these shared criteria. The study identifies which dimensions should be prioritized in chatbot evaluation and provides a structured basis for comparing platform performance. AHP organizes the criteria and translates their relative importance into comparative priorities. The findings are intended to inform the evaluation and improvement of e-commerce chatbot services in ways that reflect customer needs and expectations.

Keywords: Artificial Intelligence, E-commerce, Analytic Hierarchy Process.

How to Cite: Nikith Nannapaneni; Dr. A. V. S. Prasad (2026) Weighting Customer Perceptions of AI Chatbots in E-Commerce: An AHP-Based Evaluation Framework. *International Journal of Innovative Science and Research Technology*, 11(9), 2344-2351. <https://doi.org/10.38124/ijisrt/26sep1276>

I. INTRODUCTION

AI chatbots are increasingly integrated into e-commerce, where they provide assistance at scale and help businesses manage growing volumes of customer interactions (Chakraborty et al., 2023; Khatwani & Gupta, 2026). However, widespread adoption and operational benefits, such as scalability and lower costs, do not necessarily mean that chatbots meet customer needs (Rahevar & Darji, 2024; Trần, 2025). Evaluating these systems from a customer-centered perspective is therefore important, particularly because user-related barriers can complicate implementation (Kamoonpuri & Sengar, 2023).

To address this need, this study applies the Analytic Hierarchy Process, a framework for multicriteria decision analysis, to evaluate e-commerce chatbots from the customer's perspective (Nguyen, 2021). It compares chatbots associated with Amazon, Myntra, Meesho, Flipkart, and AJIO across five criteria: responsiveness, personalization, reliability, ease of use, and service quality (Ayswarya & T, 2026; S et al., 2026). Applying the same criteria across platforms makes it possible to identify the dimensions customers value most and compare platform performance.

AHP offers a structured way to translate qualitative customer assessments into comparative priorities that can guide chatbot development (Srivastava et al., 2024). The

approach considers technological performance alongside user expectations and service characteristics associated with customer satisfaction and platform loyalty (Balaji & Rao, 2024; Rasheed et al., 2025). Customer feedback can also highlight opportunities for improvement. For example, surveys and interaction data may reveal recurring issues, such as unresolved questions or irrelevant responses, while subsequent assessments can indicate whether changes have helped (Baabdullah et al., 2022; Kumar & Mishra, 2025). These comparisons clarify which service attributes customers prioritize and where platforms differ. Because adoption alone does not establish whether chatbot interactions meet customer expectations (Trần, 2025), this study uses AHP to assess performance beyond operational efficiency (Birje, 2026a, 2026b). It also distinguishes efficiency from customer value by considering whether interactions are responsive and empathetic to individual needs. Perceived empathy and emotionally supportive communication may influence trust, satisfaction, and purchase intentions (Baabdullah et al., 2022; Lee et al., 2021; Mari et al., 2024).

By estimating the relative importance of qualitative service attributes, the study connects chatbot functionality with user-centered requirements (Cheng et al., 2021; Ranjan & Upadhyay, 2024). Its multicriteria framework organizes subjective consumer experiences into a prioritized hierarchy, helping to identify performance gaps in current e-commerce interfaces (Lachgar et al., 2024; Vuyyuru & Prasad, 2025).

The resulting framework is intended to help businesses improve digital customer touchpoints in line with consumer-oriented quality standards (Triyana & Moeis, 2022). AHP priorities identify the most important customer-focused dimensions and provide a basis for comparing the selected chatbots. In this way, the evaluation moves beyond operational measures to consider how well digital assistance meets contemporary online consumers' expectations (Martínez et al., 2024). It also considers how specific chatbot functions may support or hinder the purchasing process (Al-Shafei, 2024; Nichifor et al., 2021).

➤ Objective of the Study

This study uses AHP to prioritize responsiveness, personalization, reliability, ease of use, and service quality, and to compare the chatbots associated with Amazon, Myntra, Meesho, Flipkart, and AJIO. High-quality digital services combine technical performance with socially appropriate, context-sensitive interaction (Asyrafah & Rufaidah, 2026). This balance matters because AI support systems must be efficient while showing enough empathy to foster customer loyalty (B et al., 2026; Kim et al., 2023). Emotional connection and social enjoyment may also encourage engagement, highlighting the importance of aligning chatbot interactions with customer motivations. Although chatbots offer round-the-clock availability and quick responses, they may struggle to match human emotional understanding and conflict resolution (Gupta & Pandey, 2026). Platforms should therefore pair accurate, dependable assistance with context-sensitive communication rather than relying on human-like cues alone. Chatbot service quality has been linked to customer loyalty through perceived value, trust, and satisfaction (Chen et al., 2023). Building trust requires both strong functional performance and high-quality interactions, as well as access to human support for complex requests.

II. LITERATURE REVIEW

Research describes the consumer–company interface as shifting toward a technology-dominant model, in which intelligent agents serve as key service channels and support consumer decision-making (Pantano & Pizzi, 2020). These interactions also need to convey relational qualities and digital empathy—not merely functional efficiency—to help build consumer–brand relationships (Günay, 2026; Pizzi et al., 2020). Studies of AI-mediated services suggest that perceived intelligence and anthropomorphism may foster empathy, strengthening perceptions of service authenticity and consumer empowerment (Zhao & Aw, 2025). These relational effects complement functional considerations: chatbot service quality has been associated with customer value, trust, satisfaction, and loyalty, while responsiveness and personalization shape the interaction experience.

Previous chatbot assessments have examined user satisfaction, task completion, conversational quality, and system performance. AHP-based research has shown how multiple criteria can be systematically weighted when comparing chatbot options. However, the literature calls for greater attention to customers' perceptions of chatbot

usefulness in e-commerce, rather than focusing primarily on organizational or technical factors (Trần, 2025). In response, this study brings customer-oriented service dimensions together in an AHP framework. Pairwise comparisons are used to represent their relative importance and assess selected platforms against shared criteria (Chakraborty et al., 2023; Nguyen, 2021).

This approach addresses a research gap in understanding how communication behaviors and language features contribute to relational outcomes in online retail (Pinxteren et al., 2020). It also recognizes that digital literacy and individual readiness to use AI may shape how customers interpret these features (Gharib et al., 2025; Pan et al., 2026). Although anthropomorphic cues may strengthen social presence and empathy, excessive humanization can heighten privacy concerns or feelings of eeriness, potentially reducing acceptance and trust (M. Song et al., 2023; S. W. Song & Shin, 2022; Truong & Chen, 2025).

III. METHODOLOGY

The Analytical Hierarchy Process (AHP) is one of the multi-criteria-decision methods (MCDM) and the decision-support framework developed by (Saaty, TL). Its main aim is to assess the relative importance of a defined set of alternatives using a ratio scale, which is based on the decision-maker's judgment. This methodology highlights the importance of the intuitive assessments made by the decision-maker and the need for consistency when comparing alternatives during the decision-making process. Since decision-makers depend on their expertise and experience to make judgments and ultimately decisions, the AHP framework is well-suited to their behavioural tendencies. A significant benefit of this method is its capacity to systematically arrange both measurable and non-measurable factors, providing a structured yet relatively simple approach to addressing decision-making issues. Additionally, by logically breaking down a problem from a broader viewpoint to more specific details, one can create links between the smaller components and the larger context through straightforward paired comparison judgments. (Saaty, TL 1980) outlined the following steps for implementing the AHP:

- Define the problem and determine its goal.
- Structure the hierarchy from the top (the objectives from a decision-maker's viewpoint) through the intermediate levels (criteria on which subsequent levels depend) to the lowest level which usually contains the list of alternatives.
- Construct a set of pair-wise comparison matrices (size $n \times n$) for each of the lower levels with one matrix for each element in the level immediately above by using the relative scale measurement shown in Table 1. The pair-wise comparisons are done in terms of which element dominates the other.
- There are $n(n-1)/2$ judgments required to develop the set of matrices in step 3. Reciprocals are automatically assigned in each pair-wise comparison.

- Hierarchical synthesis is now used to weight the eigenvectors by the weights of the criteria and the sum is taken over all weighted eigenvector entries corresponding to those in the next lower level of the hierarchy.
- Having made all the pair-wise comparisons, the consistency is determined by using the eigenvalue, $\lambda_{\max}$, to calculate the consistency index, CI as follows:

$CI = (\lambda_{\max} - n) / (n - 1)$, where n is the matrix size. Judgment consistency can be checked by taking the consistency ratio (CR) of CI with the appropriate value in Table 2. The CR is acceptable, if it does not exceed 0.10. If it is more, the judgment matrix is inconsistent. To obtain a consistent matrix, judgments should be reviewed and improved.

- Steps 3-6 are performed for all levels in the hierarchy.

Table 1 The Saaty's Scale of Relative Importance

Relative importance	Definition	Description
1	Equally importance	Two factors equally influence the objective
3	Moderate importance	Experience and judgement slightly favour one factor over another
5	Strong importance	Experience and judgement strongly favour one factor over another
7	Very strong importance	One decision factor is strongly favoured over another, and its supremacy is established in practice
9	Extreme importance	The evidence favouring one decision factor over another is of the highest possible orders of validity
2,4,6 and 8	Intermediate values between adjacent values	When compromise is required

Table 2 Average Random Consistency (RI)

Size of matrix	1	2	3	4	5	6	7	8	9	10
Random consistency	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

This investigation identified five essential evaluation criteria, which are detailed in the subsequent sections. Primary data were collected through questionnaires administered to customers between 21 and 50 years of age in Hyderabad, with responses documented as pairwise comparison matrices. A structured questionnaire instrument was employed to facilitate the data collection process. The questionnaire design was developed with meticulous attention to ensure maximum accuracy of the collected information and to enhance respondent comprehension. Subsequently, the Analytic Hierarchy Process (AHP) was applied to the gathered data to accomplish the research objectives. The AI chatbots of the five alternatives and five criteria are elaborated below.

➤ Alternatives:

- Amazon (Alexa Shopping / Rufus / AI Help) Core AI Feature: Leverages sophisticated Rufus and Alexa integrations to deliver context-aware shopping experiences, facilitate conversational product discovery, and provide comprehensive troubleshooting assistance and it demonstrates exceptional natural language processing (NLP) capabilities, maintains cross-category contextual awareness, and offers dependable voice and text support functionality.
- Flipkart (AskBot / Flipkart Commerce Cloud tech) Core AI Feature: AskBot manages order tracking, refund processing, and fundamental product inquiries through advanced NLP methodologies. It delivers expedited transactional assistance and demonstrates proficiency in localized vernacular interpretation.
- Myntra (Maya / MyStylist / MyFashionGPT) Core AI Feature: Maya (chatbot) operates in conjunction with specialized generative AI functionalities including

MyStylist and MyFashionGPT. It provides outstanding domain-specific fashion recommendations, facilitates outfit composition, and demonstrates superior intent comprehension; however, its conversational capabilities remain exclusively focused on apparel and beauty categories.

- Ajo (Reliance Conversational Assist) Core AI Feature: Incorporates integrated foundational automated support systems for order tracking, size exchanges, and return management and performs adequately for logistics and order administration.
- Meesho (Basic Support Automation) Core AI Feature: Employs rule-based and foundational NLP chatbots to address bulk inquiries concerning reselling operations, shipping logistics, and return procedures and demonstrates exceptional efficiency in resolving standard low-complexity seller and buyer inquiries at considerable scale.

➤ Criteria:

- Responsiveness refers to how quickly a chatbot acknowledges a request and provides a relevant, accurate answer, including how promptly it helps resolve a customer's problem (Baabdullah et al., 2022; Noor et al., 2021).
- Personalization measures how well the chatbot adapts its replies, recommendations, and assistance to customers' preferences, previous choices, or stated needs, rather than providing generic information (Baabdullah et al., 2022; El-Shihy et al., 2024).
- Reliability concerns consistent and dependable performance, accurate information, and delivery of the assistance the chatbot appears to promise (Meyer-Waarden et al., 2020; Yun & Park, 2022).

- Ease of use describes how easily customers can access and navigate the chatbot, communicate their requests, and complete tasks without unnecessary effort or confusion (Borsci et al., 2021; El-Shihy et al., 2024).
- Service quality captures customers' overall assessment of the interaction, including the chatbot's ability to understand requests, provide useful assistance, and resolve problems effectively (Chen et al., 2025; Trần, 2025).

Together, these criteria provide a customer-centered basis for comparing Amazon, Myntra, Meesho, Flipkart, and AJIO. The AHP framework organizes the evaluation hierarchically: the objective of improving the chatbot experience is divided into five criteria, which are then used to assess the selected platforms through pairwise comparisons. These criteria were selected because they represent complementary, observable features of chatbot interactions: timely and reliable assistance, personalized responses, ease of interaction, and overall service quality.

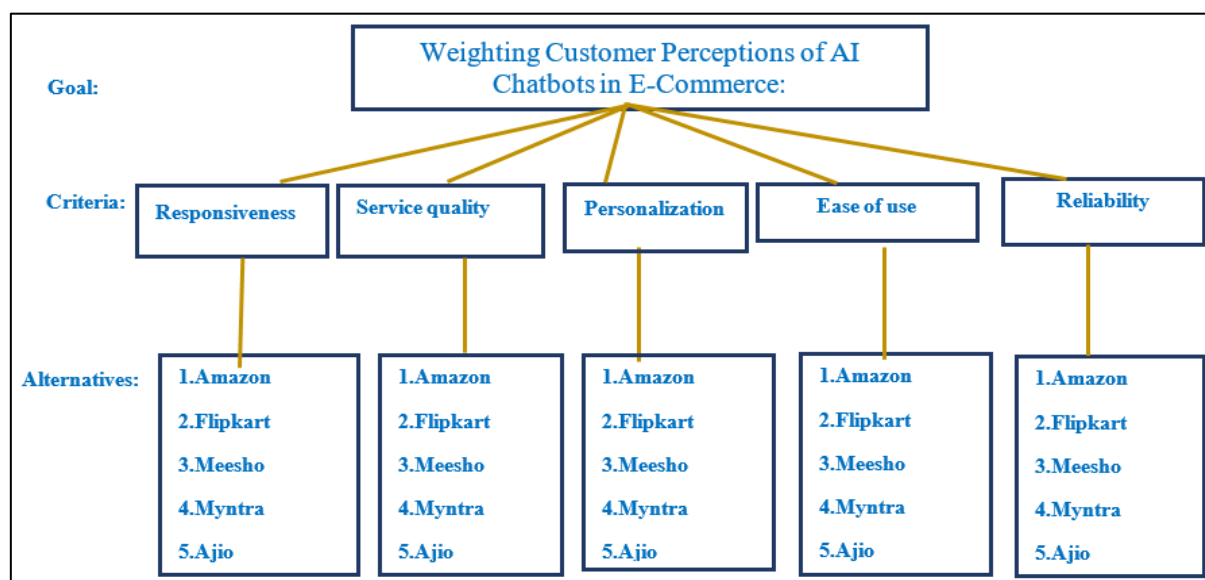


Fig 1 Proposed Model

The AHP calculations are given in Table 3 to 9

Table 3 Pair-Wise Comparison Matrix for all Criteria

	Responsiveness	Service quality	Personalization	Ease of use	Reliability	Priority vector
Responsiveness	1	2	2	2	3	0.325
Service quality	1/2	1	4	1/3	2	0.196
personalization	1/2	1/4	1	1/2	1/2	0.095
Ease of use	1/2	3	2	1	3	0.272
Reliability	1/3	2	2	1/3	1	0.112

$$\lambda_{\max} = 5.433, CI=0.108, CR = 0.097 < 0.1$$

Table 4 Pairwise Comparison Matrix for “Responsiveness “

	Flipkart	Amazon	Myntra	Meesho	Ajio	Priority vector
Flipkart	1	2	3	2	3	0.331
Amazon	1/2	1	4	4	6	0.347
Myntra	1/3	1/4	1	1/2	3	0.108
Meesho	1/2	1/4	2	1	3	0.153
Ajio	1/3	1/6	3	1/3	1	0.062

$$\lambda_{\max} = 5.353, CI=0.088 CR = 0.079 < 0.1$$

Table 5 Pairwise Comparison Matrix for “Service Quality”

	Flipkart	Amazon	Myntra	Meesho	Ajio	Priority vector
Flipkart	1	1/5	1/3	1/2	3	0.104
Amazon	5	1	1/2	2	6	0.307
Myntra	2	2	1	3	4	0.372
Meesho	3	1/2	1/3	1	4	0.163
Ajio	2	1/6	1/4	1/4	1	0.054

$$\lambda_{\max} = 5.258, CI=0.065, CR=0.06<0.1$$

Table 6 Pair-Wise Comparison Matrix for “Personalization”

	Flipkart	Amazon	Myntra	Meesho	Ajio	Priority vector
Flipkart	1	2	2	3	4	0.354
Amazon	1/2	1	3	3	5	0.307
Myntra	1/2	1/3	1	3	2	0.171
Meesho	1/3	1/3	1/3	1	2	0.100
Ajio	1/4	1/5	1/2	1/2	1	0.068
$\lambda_{\max} = 5.233, CI=0.058, CR = 0.052 < 0.1$						

Table 7 Pair-Wise Comparison Matrix for “Ease of Use”

	Flipkart	Amazon	Myntra	Meesho	Ajio	Priority vector
Flipkart	1	1/3	2	3	3	0.251
Amazon	3	1	3	2	2	0.364
Myntra	2	1/3	1	2	2	0.160
Meesho	1/3	1/2	1/2	1	2	0.128
Ajio	1/3	1/2	1/2	1/2	1	0.096
$\lambda_{\max} = 5.373 CI=0.093, CR = 0.083 < 0.1$						

Table 8 Pair-Wise Comparison Matrix for “Reliability”

	Flipkart	Amazon	Myntra	Meesho	Ajio	Priority vector
Flipkart	1	2	3	3	1/2	0.253
Amazon	1/2	1	3	2	1/3	0.166
Myntra	1/3	1/3	1	1/2	1/4	0.072
Meesho	1/3	1/2	2	1	1/4	0.102
Ajio	2	3	4	4	1	0.407
$\lambda_{\max} = 5.116, CI=0.029, CR = 0.03 < 0.1$						

Table 9 Final Priority Table

	Responsiveness	Service quality	Personalization	Ease of use	Reliability	Final priority vector	Rank
	0.325	0.196	0.095	0.272	0.112		
Flipkart	0.331	0.104	0.354	0.251	0.253	0.2582	2
Amazon	0.347	0.307	0.307	0.364	0.166	0.3197	1
Myntra	0.108	0.372	0.171	0.160	0.072	0.1758	3
Meesho	0.153	0.163	0.100	0.128	0.102	0.1374	4
Ajio	0.062	0.054	0.068	0.096	0.407	0.1088	5

IV. RESULTS

This study set out to evaluate AI chatbots in e-commerce from the customer's perspective rather than from an operational or purely technical standpoint, and to do so in a way that translates subjective consumer judgements into structured, comparable priorities. Applying the Analytic Hierarchy Process to five customer-centered criteria — responsiveness, personalization, reliability, ease of use, and service quality — across chatbots associated with Amazon, Myntra, Meesho, Flipkart, and AJIO, the analysis produced a clear ranking of both the criteria and the platforms.

The criteria weights show that customers do not value all chatbot attributes equally. Responsiveness emerged as the most important criterion with a priority of 0.325, followed closely by ease of use at 0.272. Service quality ranked third at 0.196, reliability fourth at 0.112, and personalization last at 0.095. That ordering is instructive: the attributes that customers prioritize most are those tied to the immediate, frictionless completion of a task — receiving a prompt and relevant answer, and being able to navigate and communicate with the chatbot without unnecessary effort. More advanced,

adaptive capabilities such as personalization, while valued, appear to be secondary to the basics of functional interaction. This suggests that investment in sophisticated personalization may yield fewer perceived returns than improvements to speed, accuracy, and usability, at least among the customer population studied.

At the platform level, Amazon achieved the highest final priority vector at 0.3197, ranking first overall, and it did so by leading on responsiveness (0.347) and ease of use (0.364) — the two most heavily weighted criteria. Flipkart ranked second with a final priority of 0.2582, reflecting its strong performance on responsiveness (0.331) and the highest personalization score among the platforms (0.354). Myntra followed in third place at 0.1758, distinguished by the strongest service quality score (0.372). Meesho ranked fourth at 0.1374, and AJIO fifth at 0.1088. Notably, AJIO recorded the top reliability score of 0.407, yet this advantage did not translate into a higher overall ranking because reliability carries a comparatively low weight of 0.112 — a result that illustrates how strongly the overall outcome depends on the criteria priorities customers themselves assign.

The internal consistency of the judgements supporting these results should be noted. All pairwise comparison matrices produced consistency ratios below the 0.10 threshold — CR values of 0.097 for the criteria matrix, 0.079 for responsiveness, 0.06 for service quality, 0.052 for personalization, 0.083 for ease of use, and 0.03 for reliability — indicating that the responses were sufficiently coherent for the derived priorities to be considered meaningful.

V. CONCLUSION

The central contribution of this work is methodological and practical: it offers a replicable, customer-anchored framework for evaluating e-commerce chatbots that organizes qualitative service attributes into a prioritized hierarchy. Rather than treating adoption, scalability, or cost reduction as proxies for success, the framework directs attention to what customers actually experience and value. For platform managers, the results provide a basis for targeting improvement efforts where they are most likely to matter — prioritizing responsiveness and ease of interaction while treating reliability, service quality, and personalization as complementary dimensions to be developed in a balanced way. The framework can also be reapplied periodically to track whether changes to a chatbot have altered customer priorities or platform performance over time.

Several limitations qualify these findings and point toward future work. The data were drawn from customers aged 21 to 50 in Hyderabad, so the priorities and rankings reflect a specific geographic and demographic context, and the criteria weights are inherently tied to the judgements of those respondents. The study assessed five criteria across five platforms rather than an exhaustive set, and it captures customer perceptions at a point in time rather than over a sustained period. Future research could extend the framework to broader and more diverse customer populations, incorporate additional criteria or sub-criteria, and combine AHP results with longitudinal or behavioural measures such as interaction logs and task-completion data. Linking perceived priorities to observed chatbot performance would help validate whether the dimension's customers say they value most are the ones that most strongly shape satisfaction, trust, and loyalty in practice.

Subsequent assessments ought to integrate fuzzy logic methodologies to more comprehensively address the fundamental subjectivity inherent in user-perceived satisfaction indicators, given that existing frameworks may inadequately represent complex linguistic dimensions. Additionally, prospective scholarly investigations should consider employing multi-criteria decision-making (MCDM) methodologies including PROMETHEE, Fuzzy PROMETHEE, AHP-ANP, VIKOR, TOPSIS, Fuzzy AHP, and Fuzzy TOPSIS as viable analytical instruments.

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