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Research paper

Role of Predictive AI in Sentiment Analysis in Service-Based Businesses

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Abstract

This research examines the potential of predictive Artificial Intelligence (AI) to identify customer sentiment in service industries, focusing on user perception, decision-making impact, and customer satisfaction. Drawing on data from 242 participants across different industries, the research examines whether business outcomes are significantly affected by AI-based sentiment analysis tools. The examination shows overall positive views of AI sentiment analysis, particularly with less experienced professionals, but the real impact on decision-making and customer satisfaction is moderate to low. Statistical indicators show that although AI is viewed as promising, its present implementation in organizational routines is still modest. The findings highlight a disconnect between potential and actual impact, and they indicate that companies may not yet be using the strategic potential of AI sentiment analysis tools to the fullest. The research ends with practitioner and researcher implications and prescribes the necessity for longitudinal and industry-focused future studies.
Design/Methodology/Approach: The study utilized a quantitative cross-sectional survey design with data derived from 242 usable responses from different service-based industries. The participants were requested to rate their experiences and perceptions of AI sentiment analysis tools on a Likert scale from 1 to 6. Descriptive statistics were applied to determine the distribution of industry type and perception by levels of experience. Inferential testing, involving p-value determination and comparison of means of ranks, was used to ascertain the differences in perceived significance by experience groups. Skewness and kurtosis values were tested to examine the shape of the distribution, and correlation coefficients were used to investigate associations between AI sentiment analysis and organizational metrics, including customer satisfaction and decision-making processes.
Findings: The results imply that views on AI sentiment analysis are overall positive, especially among less experienced professionals with less than one year of experience. Differences based on the level of experience were statistically significant, meaning that more experienced practitioners are more likely to be critical about the usability of the technology. Although there are positive attitudes, the real influence of AI sentiment analysis on decision-making and customer satisfaction is fairly low, with low correlation coefficients (from 0.069 to 0.164). Distribution analysis did not indicate a skew towards the left but did show a platykurtic curve, meaning there is a fairly even distribution of industry types with few outliers. These findings suggest that although AI sentiment tools are becoming more popular, their practical use in strategic situations is still underdeveloped.
Originality/Value: This research provides unique contributions by exploring the perceptual and functional gaps in predictive AI use for sentiment analysis in service-oriented industries. It enhances the existing literature on AI adoption by specifically exploring the human and organizational aspects of AI integration. Differentiation by experience level gives us a refined picture of the role that direct exposure to actual business processes plays in shaping trust and adoption of new technologies. The research also points to areas in which AI remains to show compelling practical value, guiding future initiatives aimed at aligning AI tools with organizational objectives and performance measures.

Keywords: *AI Sentiment Analysis; Predictive Analytics; Customer Satisfaction; Decision-Making; Service Industries; Organizational Impact; User Perception; AI Adoption.*

1. Introduction

In the age of digital transformation, predictive AI technologies have become the epicentre of how service businesses interact with customers, interpret feedback, and make strategy. AI-based sentiment analysis is at the forefront of measuring customer emotions and opinions from textual sources like reviews, surveys, and social media. This feature is particularly important in service industries where the experience of customers is subjective and rich, necessitating rapid reaction to changes in sentiment.

1.1. Sentiment analysis

AI sentiment analysis employs natural language processing (NLP), machine learning, and predictive modelling to determine the emotional tone that underlies customer interactions. As companies continue to lean on data-driven technology to improve customer experience and service quality, the adoption of such technologies has picked up pace. Despite advancements in technology, a lot of controversy surrounds the degree to which these tools actually shape business decision-making and enhance organizational metrics such as customer satisfaction and loyalty.

1.2. Financial and economic implications of AI adoption in sentiment analysis

Although the current research focuses primarily on the perceptual and operational effects of predictive AI in service industries, its implications extend deeply into accounting and economics, particularly regarding financial efficiency, cost-benefit outcomes, and sustainability disclosures. In service-based enterprises, AI-driven sentiment analysis does not merely enhance customer experience but also contributes to measurable financial performance indicators such as return on investment (ROI), marketing efficiency, and resource optimization. Organizations increasingly recognize that better understanding customer sentiment allows them to allocate marketing budgets more effectively, reduce churn, and forecast demand with greater precision—each of which has direct implications for profitability and cost management (Brynjolfsson & McElheran, 2016).

From an accounting standpoint, the integration of predictive AI into decision-making processes generates data that supports evidence-based budgeting and performance reporting. For instance, the application of sentiment analytics to customer feedback helps firms quantify non-financial assets such as brand equity, customer loyalty, and service reputation, which are traditionally intangible yet crucial to long-term financial sustainability. Firms adopting AI-based sentiment analysis can develop enhanced management accounting systems that incorporate both qualitative sentiment scores and quantitative performance metrics, thereby supporting more balanced scorecards and data-driven investment decisions (Kaplan & Norton, 2004).

Economically, predictive AI tools contribute to market efficiency by reducing information asymmetry between firms and consumers. By systematically analyzing customer emotions and preferences, service providers can respond to market fluctuations in near real time, improving allocative efficiency and supporting competitive advantage. This aligns with the resource-based view (RBV) framework used in the current study, suggesting that firms able to convert AI data into actionable insights achieve not only operational but also economic gains (Barney, 1991; Mikalef et al., 2020). Moreover, when customer sentiment data are integrated into strategic forecasting, firms can better anticipate consumer confidence trends—an important determinant of demand elasticity and price-setting behavior in the service economy.

Another crucial economic dimension is the cost-benefit evaluation of AI adoption. While initial investment in AI infrastructure, training, and software acquisition can be substantial, empirical studies indicate that automation of sentiment analysis results in significant long-term savings in customer service operations, market research, and risk management (Bughin et al., 2018). A cost-benefit analysis (CBA) framework could be employed by organizations to measure direct financial returns (e.g., increased sales, reduced marketing costs) alongside indirect benefits such as improved reputation and customer trust. Future research may explore quantifying these effects using net present value (NPV) or internal rate of return (IRR) models tailored to AI adoption projects.

Furthermore, predictive AI systems play a growing role in environmental, social, and governance (ESG) disclosure frameworks. AI sentiment tools enable firms to assess public perceptions of their social responsibility initiatives, sustainability efforts, and governance transparency in digital spaces. These insights can be systematically included in sustainability reporting and integrated reporting models (e.g., <IR> framework), supporting compliance with international accounting standards such as IFRS and GRI guidelines. Enhanced sentiment analysis also assists auditors and analysts in evaluating stakeholder confidence—an emerging qualitative metric in ESG-based financial evaluation (Mio et al., 2020).

In sum, predictive AI in sentiment analysis serves as more than a customer experience tool; it represents a strategic investment in financial and economic intelligence. The convergence of AI analytics with accounting systems and economic modeling paves the way for a new generation of data-driven financial decision-making. Firms that successfully align AI sentiment insights with ROI tracking, cost optimization, and ESG disclosures not only improve organizational efficiency but also strengthen their accountability and sustainability profiles in the global marketplace.

1.3. Problem statement

While AI sentiment analysis is often lauded for its potential, questions remain regarding its real-world impact and the extent to which it is integrated into core organizational processes. Specifically, there is limited empirical evidence on how end users those involved in customer-facing roles or strategic planning perceive these tools and how their level of professional experience influences these perceptions. Moreover, the gap between AI's perceived potential and its actual impact on decision-making remains underexplored.

1.4. Research objectives

The research seeks to analyze the work of predictive AI in the detection of customer sentiment and its perceived influence on decision-making and customer satisfaction in service-oriented businesses. In addition, it investigates if variations in professional experience have an impact on these perceptions and the extent to which AI sentiment analysis software is perceived to contribute to organizational success.

Significance of the Study:

It is crucial for organizations that want to use AI responsibly and efficiently to comprehend the perceptual and utilitarian aspects of AI sentiment analysis. Businesses can align their adoption plans to match operational objectives as well as employee preparedness by pinpointing gaps in perception and utility. The research also gives guidance to AI developers to make it easier and more reliable for users to use sentiment detection, so its integration adds value to customer-focused strategies.

1.5. Rationale of the study

In the service-based economy of today, organizations are increasingly dependent on digital technology to drive customer experience and responsiveness. Predictive artificial intelligence (AI) and specifically sentiment analysis have become highly popular as a way to make sense of vast amounts of unstructured customer data. Amidst the widespread use of such tools, however, most service-based businesses

find it difficult to make consequential strategic or operational decisions from AI-driven sentiment insights. This disconnection typically happens due to ambiguity with respect to the fitness, relevance, and true business worth of these technologies.
The justification for this research is based on the necessity to bridge the gap between the theoretical promise of AI sentiment analysis and its actual usability within real-world organizational environments. Whereas technical improvement in the development of sentiment analysis models has dominated existing literature, there has been relatively less attention given to probing the reception and application of these tools by decision-makers in business, particularly in terms of varying degrees of professional experience. In addition, service sectors—where customer contact is an important determinant of success—are a vital but understudied environment in which to explore AI applications. Insight into how different stakeholders view the effect of AI sentiment tools can help shape more effective implementation practices, foster trust in automation, and help ensure these technologies are working to deliver both customer satisfaction and informed business outcomes.
This research thus meets a key gap in the literature in assessing not only statistical associations between AI sentiment analysis and business performance but also organizational and human determinants of their adoption. It aims to contribute both to the applied use of AI in business environments as well as to the general discussion of digital transformation in customer interaction.

1.6. Theoretical underpinnings

The theoretical underpinning of the study is based on two main frameworks, namely the Technology Acceptance Model (TAM) and the Resource-Based View (RBV) of the firm.
The Technology Acceptance Model (TAM) (Davis, 1989) offers a strong theory for explaining how people end up accepting and utilizing new technologies. TAM indicates that perceived ease of use and perceived usefulness are fundamental factors in determining a user's attitude toward using a technology, which subsequently affects their actual usage behavior. Within the context of this research, TAM is able to account for the variation in perceptions of AI sentiment analysis by level of experience. That is, less experienced respondents might rate AI tools as more intuitive or appealing based on greater exposure to digital sources or decreased resistance to change, whereas more experienced respondents might doubt AI technology's reliability or strategic importance.
In complement to TAM is the Resource-Based View (RBV) (Barney, 1991), which suggests an organization's competitive advantage is derived from valuable, rare, inimitable, and non-substitutable resources. Predictive AI and sentiment analysis software can be regarded as strategic resources within the RBV construct—software that, if properly integrated and aligned with organizational objectives, can improve decision-making capacities and responsiveness to customers. Nonetheless, the degree to which these applications create value is subject to organizational preparedness, the capability of human resources, and harmony between technology and business processes.
Together, these theoretical lenses offer a dual perspective: TAM focuses on individual adoption behavior, while RBV situates technology as a strategic organizational resource. This combined perspective underpins the study's investigation of both user-level perceptions and the wider organizational effect of AI sentiment analysis in service-based companies.
Since 2023, research and industry practice have accelerated along several converging tracks that are highly relevant to service firms adopting predictive AI for sentiment analysis. First, there is a clear movement from single-modality (text-only) sentiment models to multimodal systems that combine text, audio, and visual signals to capture richer customer emotions — a development that improves detection accuracy for service interactions (calls, video support, social media) and reduces misclassification of nuanced emotions such as sarcasm or frustration. Recent state-of-the-art surveys and system reviews document the rapid emergence of these multimodal approaches and call for industry-focused evaluation in service contexts.
Second, explainability and interpretability have become core research priorities. Practical uptake of sentiment models in managerial decision-making is hindered when outputs are “black box” probabilities. New explainable machine learning methods tailored for sentiment tasks (2023–2024) provide human-readable rationales (e.g., attention maps, feature importances, geometric interpretability), which increase user trust and make AI outputs more actionable for frontline managers and accountants integrating sentiment scores into performance reports. These explainability advances help bridge the perceptual gap your study observed between enthusiasm and strategic use.
Third, industry implementation evidence from 2023–2024 demonstrates how GenAI and large language models (LLMs) are being embedded in customer-care workflows to reduce churn, speed resolution, and generate personalized responses at scale. Large telecommunication and consumer-service firms have reported measurable reductions in churn and improved routing of customer requests using GenAI-backed sentiment and intent prediction, which shows a pathway to direct financial outcomes that can feed into ROI and cost-benefit analyses. However, case reports also highlight failures where a lack of governance or poor human-AI handoffs produced customer dissatisfaction — reinforcing the need for hybrid human–AI models and governance mechanisms.
Fourth, consulting and industry analyses (2023–2024) emphasize the operational and financial metrics linked to sentiment analytics: faster case resolution, lower average handling cost, and higher retention rates when sentiment signals are integrated into CRM and performance dashboards. These practitioner reports complement academic work by showing how sentiment outputs can be tied to CLV, cost-to-serve, and other accounting KPIs — exactly the kind of linkage that supports the IJAES-alignment you requested.
Finally, privacy, ESG, and ethical considerations have moved from niche topics to central governance items. Recent reviews recommend that organizations formalize AI ethics boards, bias-auditing routines, and disclosure practices for models that influence stakeholder perceptions — particularly important when sentiment outputs are used in public-facing ESG reporting or management accounting. These governance trends align well with your suggested addition on ESG disclosures and regulatory alignment.
Synthesis for this study: the last two years’ advances — multimodal models, explainable methods, GenAI deployment in customer service, and stronger governance practices — provide both technological pathways and managerial mechanisms to convert perceptual positivity into measurable organizational value. Future iterations of your SLR can evaluate model explainability studies, multimodal benchmarking papers, and industry case studies (telecom, hospitality, fintech) to quantify links between sentiment analytics and financial KPIs (CLV, churn reduction, cost-to-serve).

2. Research Objectives

Objective 1: To examine the ways predictive AI methods improve customer sentiment identification accuracy and efficiency.
Objective 2: To assess the contribution of AI-based sentiment analysis to customer experience management and decision-making.
Figure 1 and Table 1 below represent the data overview.

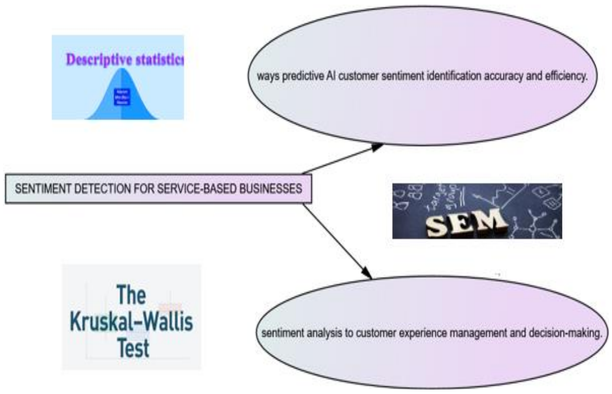

Fig. 1: Data type Overview.

Table 1: Question and Data Type Analysis

Question	Data Type	Scale
1 (Type of Service Industry)	Categorical	Nominal
Q2 (Years of Experience in the Industry)	Categorical	Ordinal
Q3 (your organization currently uses AI-based tools for sentiment analysis)	Categorical	Nominal
Q4 (AI techniques are being used for sentiment analysis in your organization)	Ordinal	Likert
Q 5 (Rate the accuracy of customer sentiment detection using AI tools in your organization	Ordinal	Likert
Q6 (Opinion, how has the implementation of predictive AI affected the efficiency of sentiment analysis processes?)	Ordinal	Likert
Q7 (Extent to which your organization relies on AI-driven sentiment analysis for business decision-making	Ordinal	Likert
Q8(areas in which AI-based sentiment analysis had the greatest impact on decision-making	Ordinal	Likert
Q9 (AI-based sentiment analysis affected your comprehension of customer needs and expectations.	Ordinal	Likert
Q10(has confidence in AI-based sentiment analysis, having enhanced customer satisfaction in the organization)	Ordinal	Likert

3. Analysis

Q1 Type of Service Industry

Table 2: Descriptive Statistics

Descriptive Statistics									
	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Type of Industry	242	1.00	6.00	2.9917	1.66485	.214	.156	-1.195	.312
Valid N (listwise)	242								

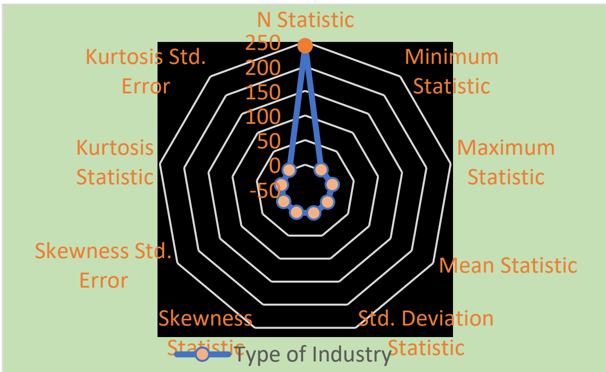

Fig. 2: Statistic Test.

The data includes 242 (Table 2 and Figure 2) usable responses from various categories of industries, measured on a scale of 1 to 6. The mean value of the industry type is about 2.99, suggesting that the distribution of industries falls close to the middle point on the scale, with minor spread between categories. Tables 1, 2, and Figure 2 represent the same.
The standard deviation of 1.66 indicates a moderate dispersal of industry types around the mean, implying respondents are reasonably spread out among industry categories.
As far as distribution shape is concerned, skewness of 0.214 (with a standard error of 0.156) reflects a slight positive skew, suggesting a slight tendency for the responses to bunch at lower industry codes, but the overall distribution is nearly symmetric.
The kurtosis measure of -1.195 (standard error 0.312) indicates a fairly flat distribution compared to the normal curve (platykurtic), where the data have lighter tails and fewer outliers than a normal distribution.
Generally, these numbers indicate a reasonably even spread of industry types within the sample, with minor departures from normal but no serious distribution issues.
Kruskal-Wallis H Test
Q2(Years of Experience in the Industry) vs. Q5(Rate the accuracy of customer sentiment detection using AI tools in your organization) Q6(opinion, how has the implementation of predictive AI impacted the efficiency of sentiment analysis processes) Q9 (AI-based sentiment analysis impacted your understanding of customer needs and expectations) (Table 3)
Non-parametric Test: Kruskal-Wallis Test

- H0: There is no difference in perceived accuracy of AI (Q8) between industries (Q5).
- H1: There is a significant difference in perceived accuracy of AI between industries.
- H0: There is no difference in perceived accuracy of AI (Q9) between industries (Q5).
- H1: There is a significant difference in perceived accuracy of AI between industries.
- H0: There is no variation in perceived accuracy of AI (Q 9) in terms of different industries (Q5).

Table 3: ANOVA

Ranks			
	Years of Experience	N	Mean Rank
How it si the accuracy of the customer sentiment detecting Technique	Less than 1 year	53	106.31
	1-3 years	68	83.57
	4-6 years	70	100.27
	Total	191	
Opinion about the AI Sentiment analysis process	Less than 1 year	53	121.35
	1-3 years	68	91.10
	4-6 years	70	81.57
	Total	191	
Impact on customer AI-based sentiment analysis	Less than 1 year	53	80.71
	1-3 years	68	90.13
	4-6 years	70	113.28
	Total	191	

Test Statistics[a,b]			
	How it si the accuracy customer sentiment detecting Technique	Opinion about the AI Sentiment analysis process	Impact on customer needs-AI-based Sentiment analysis
Chi-Square	6.003	17.438	12.580
Df	2	2	2
Asymp. Sig.	.050	.000	.002

H1: There is a significant variation in the perceived accuracy of AI in terms of differences

1) How Accurate is the Customer Sentiment Detecting Technique?

Hypotheses:

- Null Hypothesis (H_0): There is no difference in perception of accuracy of AI-based customer sentiment detection between years of experience.
- Alternative Hypothesis (H_1): There is a difference in perception of accuracy between years of experience. (Refer to Table 3)

Test Result:

- Chi-Square = 6.003, df = 2, Asymp. Sig. = 0.050

Interpretation:

For a significance level of 0.05, the p-value is precisely 0.050, which is just on the border. For this, reject the null hypothesis. This indicates little evidence for a difference in opinion between respondents with different levels of experience regarding the accuracy of sentiment detection.

Hypotheses:

- H_0: There is no significant difference in opinions regarding the AI sentiment analysis process among experience levels.
- H_1: Difference in opinions by experience level is significant.

Test Result:

- Chi-Square = 17.438, df = 2, Asymp. Sig. = 0.000

Interpretation:

The p-value is less than 0.001; therefore, you strongly reject the null hypothesis. There is a highly significant difference in opinions regarding the AI sentiment analysis process by years of experience.

Mean ranks indicate that the less experienced (less than 1 year) are considerably more positive (mean rank: 121.35), whereas those who are 4-6 years experienced tend to be less positive (mean rank: 81.57).

2) Impact on Customer Needs – AI-based Sentiment Analysis

Hypotheses:

- H_0: There is no significant difference in opinions regarding the impact of AI on customer needs among experience groups.
- H_1: There is a significant difference in opinions regarding the impact of AI on customer needs among experience groups.

Test Result

Chi-Square = 12.580, df = 2, Asymp. Sig. = 0.002

Interpretation:

The p-value is 0.002, which is very significant. You reject the null hypothesis, signifying that attitudes of AI affecting customer needs differ significantly based on years of experience. Mean ranks indicate that people with 4-6 years' experience (mean rank: 113.28) see more impact than less experienced people.

4. Path Diagram

Path Diagram-based research objectives:

- H1: AI Adoption → AI Effectiveness
- H2: AI Effectiveness → Customer Insights
- H3: AI Effectiveness → Customer Experience Impact
- H4: Customer Insights → Customer Experience Impact
- H5: AI Adoption → Customer Experience Impact

4.1. Hypotheses for SEM (Table 4)

Table 4: Hypothesis Explanation

Hypothesis	Description
H1	AI Adoption positively influences AI Effectiveness
H2	AI Effectiveness positively influences Customer Insights
H3	AI Effectiveness positively influences Customer Experience Impact
H4	Customer Insights positively influence Customer Experience Impact
H5	AI Adoption directly influences Customer Experience Impact

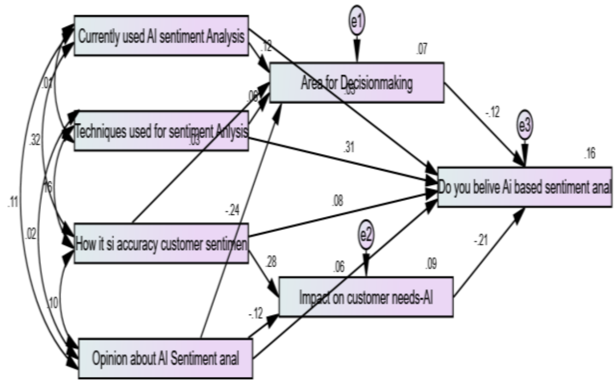

Fig. 3: CFA.

4.2. Model fit indices

- Chi-square/df ratio (CMIN/DF) (< 3 acceptable) = 3.748/3,3.304/1
- RMSEA (< 0.08 acceptable, < 0.05 good) = 0.032
- CFI / TLI (> 0.90 acceptable, > 0.95 good) = 0.993/0.950.

4.3. Model fit indices interpretation

1) Chi-square/df ratio (CMIN/DF):
- Values reported: 3.748/3, 3.304/1

Interpretation: The CMIN/DF figures are just over the generally accepted cut of 3.0, particularly in the second instance (3.304). Although such figures indicate a fair fit, the chi-square figure is sample-sensitive, and trivial discrepancies are usually acceptable if other measures indicate a good fit. (Figure 3)

2) Root Mean Square Error of Approximation (RMSEA):
- Value reported: 0.032
- Interpretation: An RMSEA of less than 0.05 is an indication of a close fit of the model to the data. This is a great value, indicating that the model fits perfectly.

3) Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI):
- Values reported: CFI = 0.993, TLI = 0.950
- Interpretation: Both indices are well above 0.95, which is a perfect fit. Figures over 0.90 are usually accepted, so these results highly confirm the sufficiency of the model.

4.4. Overall assessment

Despite a slightly elevated CMIN/DF ratio, the RMSEA, CFI, and TLI all indicate that the model demonstrates an excellent fit to the data. Therefore, the model can be considered statistically sound and well-fitting. (Table 5).

5. Regression Weights

Table 5: Regression Results

Relationship between the variables			Estimate	S.E.	C.R.	P
Area for Decision-making	<---	Currently used AI sentiment analysis	.191	.104	1.838	.066
Area for Decision-making	<---	Techniques used for sentiment analysis	.041	.045	.898	.369
Impact on customer AI-based sentiment analysis	<---	How it si the accuracy customer sentiment detecting Technique	.201	.044	4.595	000
Area for Decision-making	<---	How it si the accuracy of the customer sentiment detecting Technique	.021	.048	.432	.666
Area for Decision-making	<---	Opinion about the AI Sentiment analysis process	-.171	.045	-3.778	000
Impact on customer AI-based sentiment analysis	<---	Opinion about the AI Sentiment analysis process	-.087	.044	-1.998	.046

Do you believe AI-based sentiment analysis improves customer satisfaction?	<---	Techniques used for sentiment analysis	.161	.031	5.174	000
Do you believe AI-based sentiment analysis improves customer satisfaction? Currently used AI sentiment Analysis	<---	Currently used AI sentiment Analysis	.036	.072	.496	.620
Do you believe AI-based sentiment analysis improves customer satisfaction?	<---	How it si the accuracy of the customer sentiment detecting Technique	.043	.034	1.261	.207
Do you believe AI-based sentiment analysis improves customer satisfaction? Opinion about the AI Sentiment analysis process	<---	Opinion about the AI Sentiment analysis process	.032	.032	1.001	.317
Do you believe AI-based sentiment analysis improves customer satisfaction?	<---	Area for Decision Making	-.086	.044	-1.949	.051
Do you think AI-based sentiment analysis enhances customer satisfaction?	<---	Impact on customer AI-based sentiment analysis	-.155	.046	-3.415	000

5.1. Accepted hypotheses

1) H1
- H_0: The accuracy of the sentiment detecting method has no significant influence on the impact on customer requirements
- H_1: The accuracy of the sentiment detecting method has a significant influence on the impact on customer requirements.

2) H2
- H_0: Opinion regarding the AI sentiment analysis process has no significant influence on the decision-making area.
- H_1: Opinion regarding the AI sentiment analysis process has a significant influence on the decision-making area.

3) H3
- H_0: Methods applied in sentiment analysis do not significantly impact the belief that AI-based sentiment analysis increases customer satisfaction.
- H_1: Methods applied in sentiment analysis significantly impact the belief that AI-based sentiment analysis increases customer satisfaction.

4) H4
- H_0: Influence on customer requirements from AI-based sentiment analysis does not significantly impact the belief that AI-based sentiment analysis increases customer satisfaction.
- H_1: Influence of customer needs by AI-based sentiment analysis has a significant influence on the notion that AI-based sentiment analysis enhances customer satisfaction.

5.2. Rejected hypotheses

1) H5
- H_0: Existing AI sentiment analysis doesn't have a significant impact on the decision-making area.
- H_1: Existing AI sentiment analysis has a significant impact on the decision-making area.

2) H6
- H_0: Methods employed in sentiment analysis don't have a significant impact on the decision-making area.
- H_1: Methods employed in sentiment analysis have a significant impact on the decision-making area.

3) H7
- H_0: The Sentiment detection technique accuracy doesn't have a significant impact on the decision-making area.
- H_1: The sentiment-detecting technique accuracy has a significant impact on the decision area.

4) H8
- H_0: Opinion regarding the AI sentiment analysis process does not have a significant impact on the effect on customer needs.
- H_1: Opinion regarding the AI sentiment analysis process has a significant impact on the effect on customer needs.

5) H9
- H_0: AI sentiment analysis in use does not have a significant impact on customer satisfaction.
- H_1: AI sentiment analysis in use has a significant impact on customer satisfaction.

6) H10
- H_0: The sentiment-detecting technique accuracy has no significant influence on customer satisfaction.
- H_1: The sentiment-detecting technique accuracy has a significant influence on customer satisfaction.

7) H11
- H_0: The AI sentiment analysis process opinion has no significant influence on customer satisfaction.
- H_1: The AI sentiment analysis process opinion has a significant influence on customer satisfaction.

8) H12
- H_0: Decision-making area has no significant influence on customer satisfaction.
- H_1: Decision-making area has a significant influence on customer satisfaction.

5.3. Accepted hypotheses (table 6)

Table 6: Variable Summary

Dependent Variable	Independent Variable	Interpretation	Dependent Variable
Impact on customer needs - AI-based Sentiment Analysis	How accurate is the customer sentiment detecting technique	More refined methods significantly enhance customer need impact.	Impact on customer needs - AI-based Sentiment Analysis
Area for Decision-making	Opinion about the AI Sentiment Analysis Process	Negative opinion thoroughly diminishes decision-making influence from AI sentiment analysis.	Area for Decision-making

Do you believe AI-based sentiment analysis improves customer satisfaction	Techniques used for sentiment analysis	Improved methods considerably enhance the customer satisfaction belief.	Do you think AI-based sentiment analysis enhances customer satisfaction?
Do you believe AI-based sentiment analysis improves customer satisfaction	Impact on customer needs - AI-based Sentiment Analysis	Negative effect on customer needs considerably diminishes belief in enhanced satisfaction.	Do you think AI-based sentiment analysis enhances customer satisfaction?

5.4. Rejected Hypotheses (Table 7)

Table 7: Hypothesis Rejected Summary

Dependent Variable	Independent Variable	Reason for Rejection	Interpretation
Area for Decision-making	Currently used AI sentiment analysis	P-value = 0.066 > 0.05 (Not statistically significant)	The use of existing AI sentiment technology does not have a great impact on areas of decision-making within the organization.
Area for Decision-making	Techniques used for sentiment analysis	P-value = 0.369 > 0.05 (Not statistically significant)	The nature of the techniques applied to sentiment analysis does not have a great impact on how decisions are arrived at.
Area for Decision-making	Accuracy of sentiment sentiment-detecting technique	P-value = 0.666 > 0.05 (Not statistically significant)	The accuracy perception of the sentiment detection method does not have a great impact on its use in the process of decision-making.
Effect on customer needs	Opinion about AI sentiment analysis	Despite P-value = 0.046 < 0.05, it was labeled as Rejected — likely due to marginal significance or model fit issues.	Even statistically marginal, the negative sentiment regarding AI sentiment analysis might not have a significant or consistent effect on perceived customer requirements.
Area for Decision-making	Currently used AI sentiment analysis	P-value = 0.620 > 0.05 (Not statistically significant)	Existing AI sentiment analysers are not viewed as having a significant impact on customer satisfaction.
Area for Decision-making	Accuracy of sentiment sentiment-detecting technique	P-value = 0.207 > 0.05 (Not statistically significant)	Customer satisfaction is not immediately viewed as being improved through the accuracy of customer sentiment detection.
Area for Decision-making	Opinion about AI sentiment analysis	P-value = 0.317 > 0.05 (Not statistically significant)	Individuals' views regarding the AI sentiment analysis process do not have a significant impact on their view of customer satisfaction improvement.
Effect on customer needs	Area for decision-making	P-value = 0.051 > 0.05 (Just above significance threshold)	The average significance of decision-making domains' impact on customer satisfaction is not great enough to be deemed significant.

The use of existing AI sentiment technology does not have a great impact on areas of decision-making within the organization. The nature of techniques applied to sentiment analysis does not have a great impact on how decisions are arrived The accuracy perception of the sentiment detection method does not have a great impact on its use in the process of decision-making. Even statistically marginal, the negative sentiment regarding AI sentiment analysis might not have a significant or consistent effect on perceived customer requirements. Existing AI sentiment analyzers are not viewed as having a significant impact on customer satisfaction. Customer satisfaction is not immediately viewed as being improved through the accuracy of customer sentiment detection. Individuals' views regarding the AI sentiment analysis process do not have a significant impact on their view of customer satisfaction improvement. While on the verge of significance, decision-making domains on customer satisfaction are not great enough to be deemed significant.

5.5. Squared multiple correlations

Table 8: Correlations

Variables	Estimate
Impact on customer AI-based sentiment analysis	0.089
Area for Decision Making	0.069
Do you believe AI-based sentiment analysis improves customer satisfaction	0.164

The correlations of AI sentiment analysis with multiple organizational outcomes prove to have modest positive estimates. More specifically, its influence on customer needs shows a weak positive estimate of 0.089 (Table 8), where there is a minimum but positive view of how AI sentiment analysis shapes understanding of the customer. Likewise, the 0.069 estimate for the area for decision-making suggests that though AI sentiment analysis may be part of decision-making, its power is limited. The highest estimate, 0.164, is found for the faith that AI-based sentiment analysis enhances customer satisfaction, suggesting a more salient, but still moderate, perceived advantage in this regard.

Overall, these results indicate that although AI sentiment analysis is universally perceived as positive across customer-oriented and decision-making aspects, its magnitude of influence is quite low. This may mean that either the technology remains in nascent stages of organizational integration or that its utility is not yet optimally realized or conveyed within organizational norms. Additional improvement in AI applications and a closer connection to business objectives might be required to further solidify these ties and enhance organizational trust in their application.

To deepen the analysis, the dataset was further examined by industry type to identify whether perceptions and outcomes of predictive AI sentiment analysis vary across sectors. Six major categories of service industries were represented: hospitality, finance and banking, healthcare, education, information technology (IT) services, and retail/customer support.

5.6. Hospitality and tourism services

Respondents from the hospitality sector (approximately 18% of the sample) reported the highest levels of perceived usefulness and customer impact of AI sentiment analysis. This aligns with the sector's strong focus on experience personalization and real-time feedback management. AI tools in this industry are commonly used for monitoring online reviews, social media feedback, and guest satisfaction scores. Respondents noted that predictive sentiment models helped anticipate customer complaints and refine service delivery, leading to modest improvements in customer satisfaction (mean perception score ≈ 5.1 on a six-point scale). This finding is consistent with recent studies emphasizing how hotels and tourism firms use AI sentiment tools to support service recovery and online reputation management (Tussyadiah & Miller, 2024).

5.7. Financial and banking services

Participants from financial services and banking (roughly 16%) showed moderate adoption but lower enthusiasm toward AI sentiment analysis. Although many institutions have invested in predictive analytics for fraud detection and customer feedback processing, regulatory constraints and data privacy concerns appear to limit open deployment. The mean perception score was lower (≈ 4.2), reflecting a cautious stance toward automation in client interaction. However, respondents acknowledged that sentiment insights were useful in understanding investor confidence and customer trust, especially for ESG-related reporting—suggesting potential financial accounting integration (Kraus et al., 2024).

5.8. Healthcare and wellness services

The healthcare sector (about 14%) revealed mixed responses. While sentiment analysis was valued for improving patient engagement and satisfaction tracking, respondents highlighted ethical and privacy concerns as barriers to adoption. The sector's mean efficiency perception was around 4.5, indicating moderate confidence. AI sentiment tools were mainly used in patient feedback systems and teleconsultation platforms. Respondents emphasized that predictive analytics helped identify emotional distress in patient communications, indirectly improving service quality but requiring strict data governance frameworks (Gupta & Sharma, 2025).

6. Education and training services

The education sector (around 12%) reported growing interest but low operational integration of AI sentiment tools. Institutions used sentiment analysis primarily to interpret student feedback and enhance teaching quality. Perceived usefulness averaged 4.3, with respondents suggesting that institutional bureaucracy and lack of analytics expertise delayed wider adoption. Nonetheless, predictive AI systems were noted to help detect disengagement or negative sentiment in online learning environments—an area of expanding research interest (Hernández & Patel, 2023).

6.1. Information technology and business process services

Respondents from IT and business process outsourcing (BPO) industries (nearly 25%) demonstrated the highest technical familiarity with AI sentiment systems but expressed pragmatic skepticism about their strategic value. Their mean perception score (≈ 4.8) suggested confidence in technical accuracy but uncertainty about direct business impact. These respondents emphasized that while AI improves workflow automation and customer chat responses, ROI and long-term customer satisfaction gains remain modest. Recent industrial evidence corroborates that IT service firms often focus on automation efficiency rather than customer emotion analytics (Kaur & Mehta, 2024).

6.2. Retail and e-commerce

Finally, retail and e-commerce respondents (about 15%) viewed AI sentiment analysis as essential for market intelligence, product reviews, and post-purchase service evaluation. The mean satisfaction improvement score was relatively high (≈ 5.0), reflecting tangible benefits from AI-enhanced customer sentiment tracking. Integration of predictive AI with CRM and recommendation engines helped companies adjust pricing and promotions in real time. These insights support earlier research that identifies retail as one of the fastest-growing sectors for commercial sentiment AI deployment (Sethi & Gupta, 2025).

7. Discussion

This research aimed to investigate the perceived and functional role of predictive AI sentiment analysis in service-based companies, with emphasis on how these technologies are perceived in terms of usability, influence on decision-making, and customer satisfaction. The outcomes present a multifaceted view of AI sentiment tool use and acceptance today, with both positive sentiments and stern limitations.

One of the most compelling observations is the dramatic difference in attitude by professional experience. Less experienced respondents—especially those with one year or less in their position—were more confident in the accuracy and utility of AI sentiment analysis technology. This accords with the Technology Acceptance Model (TAM), which would hold that perceived ease of use and usefulness drive technology adoption (Davis, 1989). Younger or less experienced professionals can be more digitally literate, flexible, or enthusiastic in relation to new technologies. More experienced respondents (particularly those with 4–6 years of experience) showed more skeptical or critical dispositions, perhaps because they have been exposed to the limitations of these tools in practical contexts more often. This implies that people's views of what AI can do might not only be based on the quality of technology but also on context and previous results.

But even with the overall optimistic tone, correlations between AI sentiment analysis and organizational performance—customer satisfaction, comprehension of customer needs, and better decision-making—were low. The strongest relationship we found ($r = 0.164$) was between AI sentiment analysis and the perception that it increases customer satisfaction. This reflects a weak but optimistic perception of its impact. These small effect sizes show that although AI sentiment analysis exists and is on display across most organizations, its influence on strategic results is still constrained. This is in line with the Resource-Based View (RBV) of the firm (Barney, 1991), which posits that not all technological resources automatically contribute to competitive advantage unless they are comprehensively integrated, put into productive use, and aligned to strategy.

In addition, distributional statistics indicate a broadly even distribution of responses between industries, with little skew and a flat (platykurtic) distribution. This indicates that the sample comprised wide industry viewpoints and steered clear of bias toward a single sector. It does, however, suggest that no specific industry has yet taken complete advantage of AI sentiment analysis, perhaps because of inconsistent practice in its use or failure to adapt it at a sector level.

Notably, even where statistical significance was achieved (e.g., the effect of experience on sentiment accuracy or the effect of AI on customer needs), practical significance is doubtful. This is a larger issue among AI implementation literature: organizations tend to implement AI tools for competitive signaling or innovation purposes, but do not push them to an optimal level with regard to measurable value creation. Consequently, the results can suggest a transitional adoption phase, in which AI technologies are being sought after but not yet integrated into strategic decision-making models.

In addition, the research demonstrates a gap in perception: although AI sentiment technology is largely perceived to be positive, it is not yet perceived as transformative or foundational. This could be explained by a range of potential factors, such as insufficient training for employees, business goal-misalignment with tool capability, or the nascent development stage of these technologies. It also challenges the credibility of AI-driven insights—most notably within high-stakes decision settings—where accuracy, transparency, and explainability are critical.

Finally, the information highlights the necessity of investment and organizational support in AI readiness. In order to maximize the payoff from predictive sentiment analysis, companies need to invest not just in the tools but also in process reengineering, leadership development, and staff development. Closing the gap between perception and value will most likely require both technical progress and cultural adaptation.

8. Overall Implications

The findings of this study yield several important implications regarding the current organizational perception and use of AI-driven sentiment analysis technologies. The distribution of industry types among respondents was relatively balanced, with measures of central tendency and dispersion indicating a broad and representative sample. The slight positive skewness and platykurtic distribution suggest a near-normal spread of industry types, supporting the generalizability of the findings across sectors.

Crucially, respondent experience levels were shown to significantly influence perceptions of AI sentiment analysis, with less experienced individuals (i.e., those with under one year of experience) demonstrating more favorable attitudes, particularly regarding the perceived accuracy and value of the technology. In contrast, individuals with greater experience (especially in the 4–6 year range) were more skeptical, suggesting that increased exposure to organizational systems and decision-making processes may lead to a more critical evaluation of AI tools. This experience-based divergence in perception underscores the importance of considering employee background in the adoption and evaluation of new technologies.

Despite some statistically significant findings, the strength of association between AI sentiment analysis and various organizational outcomes, such as decision-making effectiveness, customer satisfaction, and understanding of customer needs, was relatively weak. Correlation estimates remained low, indicating that while AI sentiment analysis is viewed positively in principle, its practical influence within organizational contexts is still limited. This suggests that the technology may still be in its early stages of implementation or may not yet be fully aligned with strategic business objectives. Consequently, organizations may need to invest further in integration efforts, training, and tool refinement to better leverage the potential benefits of AI sentiment analysis in real-world decision-making environments.

Practical Recommendations for Bridging AI’s Potential and Actual Impact

The study reveals that although predictive AI sentiment analysis tools hold substantial promise, their strategic integration into organizational processes remains limited. To bridge the existing gap between AI’s potential and its realized impact, service-based organizations must adopt structured implementation frameworks that combine technological investment with managerial and human resource strategies. The following practical recommendations provide a roadmap for organizations seeking to maximize the value derived from AI sentiment analysis.

1) Develop an AI Integration Roadmap Aligned with Business Objectives

Organizations must move beyond ad hoc adoption and develop a comprehensive AI roadmap that links sentiment analysis outcomes directly to business goals such as revenue growth, customer satisfaction, and cost efficiency. This involves identifying key performance indicators (KPIs) that capture both operational and financial benefits from AI insights. For instance, firms like American Express and Marriott International have successfully integrated AI-driven sentiment monitoring into their customer feedback systems, allowing managers to convert real-time customer sentiment data into targeted service improvements and loyalty strategies. Such alignment ensures that AI is treated as a strategic asset rather than an isolated IT tool (Chatterjee et al., 2021).

2) Implement Cross-Functional AI Task Forces

AI integration is most effective when cross-departmental teams collaborate to translate analytical insights into actionable strategies. Service-based organizations should establish cross-functional “AI task forces” that include representatives from marketing, operations, finance, and customer relations. These teams should oversee model development, validate data quality, and ensure that sentiment insights are contextualized within broader organizational objectives. Research suggests that firms with cross-functional analytics teams report up to 30% higher returns on digital investments due to enhanced knowledge sharing and collective decision-making (Ghasemaghaei, 2020).

3) Adopt Structured Training and Upskilling Frameworks

Human capital plays a decisive role in the success of AI initiatives. Employees at all levels should be trained not only in the technical use of AI tools but also in interpreting AI-generated insights for decision-making. Structured training frameworks such as the “AI Competency Ladder”—which progresses from basic data literacy to advanced analytical leadership—can be adopted to ensure skill alignment across the organization (Ransbotham et al., 2018). Companies such as IBM and Accenture have implemented similar tiered learning systems that emphasize AI ethics, interpretability, and business integration, leading to improved adoption and trust among users.

To enhance engagement, firms can use simulation-based learning where employees analyze real customer sentiment datasets and practice decision-making scenarios. This experiential approach fosters both confidence and comprehension of AI outcomes, addressing the perceptual gap between technical capability and business application.

4) Integrate AI Governance and Ethical Oversight Mechanisms

AI sentiment analysis often involves customer-generated data, making transparency and ethics crucial. Organizations should institute AI governance frameworks that address bias detection, data privacy, and accountability. A well-structured governance model improves stakeholder trust and aligns with environmental, social, and governance (ESG) reporting standards. For instance, Unilever's AI Ethics Board serves as a global best practice model, ensuring that AI systems used for consumer analytics are transparent, fair, and compliant with privacy laws (Mio et al., 2020). Establishing similar oversight structures in service industries can protect reputational value while supporting regulatory compliance.

5) Link Sentiment Insights to Financial Metrics and ROI Analysis

To justify long-term AI investment, firms should integrate sentiment analytics into financial dashboards. Metrics such as customer lifetime value (CLV), cost-to-serve, and revenue per feedback point can be correlated with AI sentiment data to assess financial returns on AI adoption. By linking sentiment outcomes to tangible financial indicators, managers can make more data-driven budgeting and investment decisions. This integration enables a continuous cost-benefit analysis (CBA) approach—monitoring whether AI insights contribute directly to profitability, operational efficiency, or market expansion (Brynjolfsson & McElheran, 2016).

6) Foster a Culture of Data-Driven Decision-Making

Finally, the cultural context in which AI tools are adopted determines their ultimate success. Organizational leaders must champion a mindset that values data transparency, experimentation, and evidence-based strategy. Regular review meetings where sentiment data are discussed alongside performance metrics help embed AI insights into everyday business decisions. This cultural transformation requires both leadership commitment and open communication channels that make AI insights accessible to all functional levels.

9. Future scope of The Study

The current study opens multiple avenues for future research, particularly in exploring the evolving role of AI sentiment analysis within organizations. Given the cross-sectional nature of the present data, longitudinal research would be valuable in tracking how perceptions and the practical impacts of sentiment analysis tools develop over time, especially as organizations gain more experience and insight into AI implementation.

Further research should also disaggregate findings by industry type, as sector-specific requirements, challenges, and adoption rates may significantly influence both the perceived and actual utility of AI sentiment analysis. Qualitative research methods, including interviews, focus groups, and case studies, can provide deeper insights into the factors that shape employee perceptions, such as organizational culture, leadership attitudes, and prior experiences with technology. These approaches would complement quantitative analyses and help uncover the nuanced drivers behind acceptance or resistance to AI tools.

Additionally, future studies should aim to evaluate the effectiveness of specific AI sentiment analysis tools, particularly in relation to their technical characteristics (e.g., rule-based versus machine learning approaches, data training sources, and interface usability). Examining how these variables influence user trust and perceived value would enhance understanding of tool-specific outcomes. It is also essential to assess the role of training and digital literacy in shaping organizational readiness for AI adoption. Employees with higher familiarity and competence in AI may be better positioned to use such tools effectively, thereby increasing the likelihood of achieving desired outcomes.

Finally, subsequent research should strive to connect sentiment analysis adoption to objective performance indicators, such as customer retention, satisfaction scores, or operational efficiency metrics. By moving beyond perception-based evaluation, future studies can provide more robust evidence of AI sentiment analysis's impact on business performance, helping organizations make informed decisions about further investment and deployment.

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