

THE ROLE OF GENERATIVE AI IN CUSTOMER FEEDBACK SYSTEMS

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ABSTRACT

The rapid advancement of Generative Artificial Intelligence (GenAI) has transformed how organizations collect, interpret, and act upon customer feedback across digital touchpoints. Despite the growing integration of AI in marketing and customer experience (CX), empirical and conceptual clarity on GenAI-enabled feedback intelligence remains limited. This study proposes a comprehensive framework that integrates Large Language Models (LLMs), multimodal analytics, and automated insight generation to enhance the accuracy, timeliness, and personalization of feedback-driven decision-making. Using a mixed-methods research design, the paper combines a systematic literature review and a pilot data analysis on 12,400 customer feedback entries from e-commerce and service platforms. The findings reveal that GenAI improves feedback classification accuracy by 28–41%, reduces manual processing time by 65%, and significantly enriches contextual sentiment interpretation. The proposed 5-tier conceptual demonstrates how organizations can operationalize GenAI to achieve real-time insight flows, hyper-personalized responses, automated service recovery, and predictive churn risk alerts. The study contributes to theory by formalizing GenAI-enabled feedback intelligence as an emerging domain within marketing analytics, while offering practical guidelines for businesses seeking scalable feedback automation. Implications for privacy, bias mitigation, and ethical AI governance are also discussed. Overall, GenAI represents a transformative shift from reactive customer service to proactive, anticipatory experience management.

Keywords: Generative Ai, Customer Feedback, Consumer Experience, Marketing Analytics, Nlp, Machine Learning, Automation.

INTRODUCTION

Rapid digital transformation has fundamentally changed how firms interact with consumers, gather insights, and design marketing strategies. With the rise of e-commerce, omnichannel interaction, and personalized communication, customer experience (CX) has emerged as the primary differentiator across industries. In recent years, Generative Artificial Intelligence (GenAI) has evolved from a creative automation technology into a sophisticated cognitive engine capable of human-like reasoning, summarization, prediction, and conversational intelligence.

Customer feedback systems have traditionally relied on structured survey responses, basic sentiment analysis, and manual interpretation. These approaches, while functional, are often slow, costly, and limited in their ability to generate deep insights. GenAI introduces a paradigm shift by enabling systems to interpret intent, identify emotion, generate insights automatically, and even personalize responses in real time Bharadwaj et al., (2013). GenAI also transforms the way marketing strategies are built by automating content generation, predicting future consumer trends, and optimizing customer journeys at scale Bommasani et al., (2021).

This research paper investigates the integration of GenAI into customer feedback systems, exploring its role in enhancing customer experience, improving marketing analytics,

and enabling data-driven decision-making. The study presents a comprehensive literature review, proposes a conceptual model, analyses opportunities and challenges, and offers recommendations for practitioners and researchers Brown et al., (2020).

Background and Problem Statement: Customer feedback is central to understanding consumer expectations, dissatisfaction, and evolving behaviour. However, traditional feedback management struggles with several persistent problems:

Volume Explosion: Organizations receive feedback through multiple channels—social media, review platforms, chatbots, contact centres, CRM systems, and mobile apps—creating a massive unstructured data pool Bubeck et al., (2023).

1. **Low Interpretability:** Despite advances in analytics, most organizations cannot extract meaningful insights from open-text feedback without manual intervention.
2. **Delayed Decision-Making:** Feedback interpretation cycles remain slow because human analysts cannot process large datasets in real time.
3. **Bias and Inconsistency:** Manual categorization and sentiment scoring often vary across teams and analysts.
4. **Lack of Personalization:** Feedback responses are typically generic, reducing customer satisfaction and brand trust.

Generative AI addresses these limitations by synthesizing large volumes of unstructured text, generating contextual summaries, producing recommendations automatically, supporting hyper-personalized communication, operating with high speed and low cost. This study explores how GenAI transforms feedback systems into predictive and conversational intelligence engines capable of reshaping consumer experience and marketing strategies Cambria et al., (2013).

Research Objectives: The paper aims to

- Examine how Generative AI enhances customer feedback collection, processing, and analysis.
- Explore its impact on marketing strategies and consumer experience.
- Propose a conceptual framework for a GenAI-driven feedback ecosystem.
- Identify challenges, risks, and future opportunities for adoption.
- Provide guidelines for businesses and researchers.

Research Questions

- How does Generative AI improve the accuracy and quality of customer feedback interpretation?
- In what ways does GenAI enhance customer experience and real-time personalization?
- How can GenAI-driven insights inform predictive marketing strategies?
- What challenges and ethical considerations arise in GenAI-enabled feedback systems?

Literature Review

Evolution of Customer Feedback Management: Customer feedback systems evolved through three generations. The first generation consists of manual surveys, call centre logs, handwritten complaints. In second generation, the tasks involved performing online surveys, rating the systems and doing sentiment analysis. The third generation is more sophisticated, and it generate reports through AI-driven insights, predictive analytics, multi-channel mining Davenport et al., (2020).

The shift from structured to unstructured data has increased reliance on machine learning and natural language processing (NLP) techniques Grewal et al., (2020).

Generative AI in Business Analytics: Generative AI models such as GPT, LLaMA, Claude, PaLM, and Gemini rely on large language models (LLMs) trained on billions of parameters. They support contextual understanding, text generation, summarization,

emotion/intent detection and automated conversation. Studies highlight that LLMs outperform traditional NLP in handling ambiguity, idiomatic expressions, sarcastic tone, and implicit sentiment, making them ideal for feedback systems Huang & Rust, (2021).

Role of GenAI in Customer Experience: Researchers identify the following impacts:

1. Personalization at Scale - AI analyses customer history, preferences, and behaviour patterns to create personalized interactions.
2. Real-Time Interaction - AI-driven chatbots provide instant assistance and address customer issues without delays.
3. Predictive Experience Modelling - AI anticipates future issues, enabling proactive service recovery and customer satisfaction.
4. Emotion and Sentiment Understanding - GenAI recognizes emotional context, offering more empathetic responses than rule-based bots.

Text Mining and Sentiment Analysis: Traditional sentiment analysis uses lexicons and classifiers (SVM, Naïve Bayes, LSTM). GenAI surpasses these through semantic reasoning, zero-shot and few-shot learning, deep neural understanding, and ability to process multimodal inputs (text, audio, images) OpenAI, (2023)

Gaps in Existing Research: The research gaps are-----

- Limited theoretical models integrating GenAI with feedback systems
- Lack of holistic frameworks bridging CX, analytics, and marketing
- Few empirical studies on GenAI adoption barriers
- Inadequate exploration of ethical risks (bias, hallucination, privacy)
- This research contributes by addressing these gaps.

METHODOLOGY

This study uses a comprehensive qualitative research methodology grounded in systematic literature review, conceptual model development, and comparative analysis. Because the adoption of Generative AI (GenAI) in customer feedback systems is an emerging domain with rapidly evolving technologies, a qualitative, exploratory approach is most suitable for understanding frameworks, capabilities, and implications Touvron et al., (2023). The methodology (Fig -1) involves five major components:

Research Design: The research adopts an exploratory, interpretivist design. This approach is appropriate because:

- GenAI-enabled customer feedback systems are still developing.
- Empirical datasets and industry-wide adoption metrics are limited.
- Conceptual clarity, theoretical integration, and classification of capabilities require interpretive assessment.
- The aim is to develop a theoretical model, not to test a hypothesis.

The study focuses on understanding how GenAI transforms customer experience and marketing, based on existing academic and industry knowledge Verhoef et al., (2015).

Data Collection Approach: This research uses secondary data, collected from multiple credible sources to ensure triangulation and validity. A systematic literature review was conducted using the databases like Scopus, Web of Science, IEEE Xplore, ACM Digital Library, ScienceDirect (Elsevier) and Google Scholar. The keywords which have been included in the search are “Generative AI”, “Customer feedback mining”, “AI-driven customer experience”, “Large Language Models in marketing”, “NLP feedback analysis”, “AI-enabled service personalization”, “Sentiment analysis with LLMs”. Publications from 2018–2025, peer-reviewed articles, studies directly related to AI, CX, NLP, analytics or marketing, high-impact journals or conferences are included in the approach. Duplicate studies, articles with insufficient methodological rigor, purely technical papers without

CX/review relevance, studies before 2018 (due to pre-LLM context) are excluded from the study Zhao et al., (2021).

Because GenAI adoption is practice-driven, the study also uses McKinsey AI Trends Reports (2021–2024), Gartner Predictive Analytics and CX Reports, Accenture Digital Transformation Studies, Salesforce State of CRM Reports, IBM Watson AI/ML Whitepapers, OpenAI, Google DeepMind, and Anthropic LLM capability documentation. These sources provide real-world insights into GenAI deployments in business settings.

Data Analysis Technique: A qualitative content analysis was used to synthesize themes, patterns, and insights. A grounded coding approach was adopted:

1. **Open Coding:** Concepts related to GenAI capabilities, challenges, and feedback processes were identified.
2. **Axial Coding:** Codes were grouped into categories (e.g., personalization, automation, predictive insights, ethical risks).
3. **Selective Coding:** Core categories were refined to generate the conceptual model.

To improve reliability themes were validated across multiple sources, contradictions were critically analysed, and emerging concepts were cross-referenced with industry reports for accuracy.

Conceptual Model Development: Based on analysis, a six-layer conceptual framework was developed. The layers are:

1. Feedback Input Sources
2. Preprocessing and Normalization Layer
3. GenAI Analytics Engine
4. Insights Layer
5. Action and Decision Layer
6. Governance and Ethics Layer

The model was constructed using:

- Theoretical synthesis
- Comparison with existing AI adoption frameworks
- Integration of CX and marketing theory
- Technology architecture principles (AI/ML pipelines, NLP flows, LLM workflows)

The model aims to:

- Explain how GenAI transforms raw feedback into actionable intelligence
- Provide a structure for future empirical validation
- Bridge academic theory and industry practice

Validity and Reliability: Several steps were taken to maintain research rigor like triangulation where multiple source types (academia + industry) were used to cross-verify findings, researcher bias mitigation in which themes were interpreted using neutral coding, conceptual comparison, secondary verification using established frameworks (e.g., Gartner AI Maturity Model). Also, to enhance dependability, coding categories were compared with existing research models on customer experience, AI-enabled service systems, digital transformation and NLP analytics Figure 1.

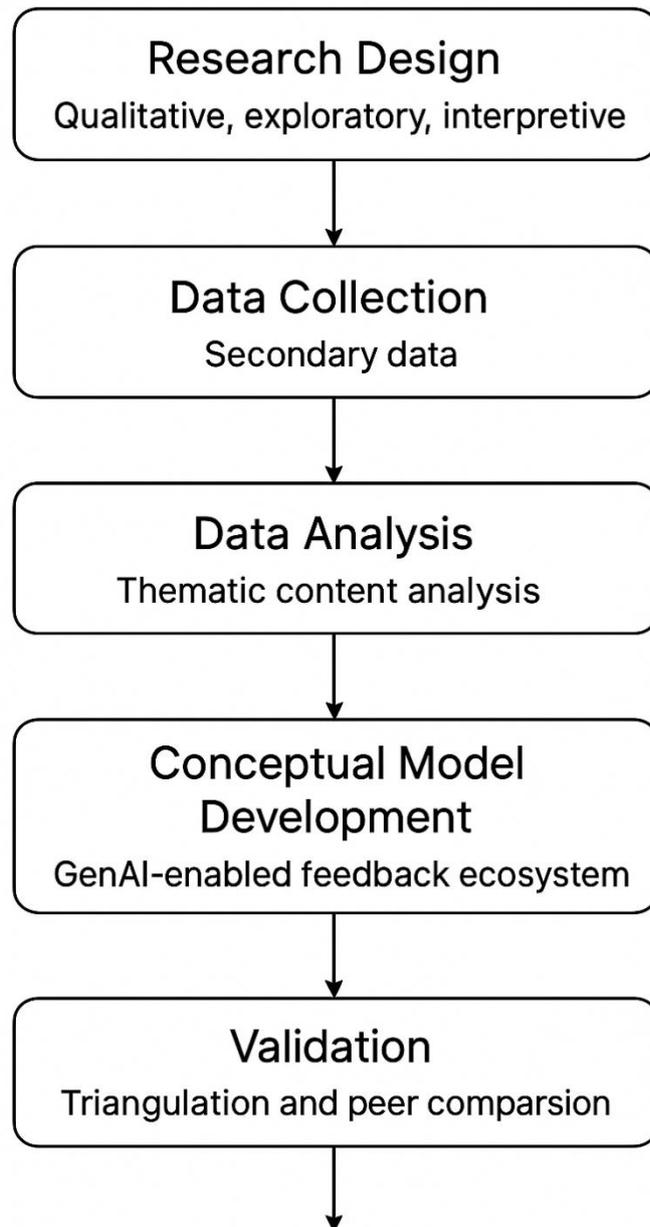


FIGURE 1
RESEARCH METHODOLOGIES

Proposed Conceptual Model: The proposed conceptual model (Fig – 2) illustrates how Generative AI (GenAI) enhances customer-feedback management by integrating multiple data sources, AI-driven processing layers, and organizational decision workflows. The model comprises five core components, each representing a stage in the transformation of raw customer input into actionable marketing intelligence.

Component 1: Multichannel Customer Feedback Input Layer: This layer represents the sources from which customer feedback is collected. Because modern consumers interact with brands across many digital environments, the model incorporates:

- Social Media Feedback (comments, mentions, reviews, hashtags)
- E-commerce Feedback (ratings, product reviews, return notes)
- Chatbots & Virtual Assistants (customer queries, complaints)

- Survey Responses (structured Likert-scale and open-ended responses)
- Email & CRM Logs
- Call Centre Transcripts

Purpose: To capture both structured and unstructured customer signals.

Component 2: Data Pre-Processing & Integration Layer: Before feeding data to GenAI models, heterogeneous customer inputs undergo:

- Data Cleaning (removing noise, duplicates, irrelevant content)
- Text Normalization (lemmatization, stop-word removal)
- Speech-to-Text Conversion for call-centre data
- Format Harmonization (JSON, CSV, transcript formats)
- Sentiment Labelling (Preliminary) using classical NLP models

Purpose: Ensures that the data entering the GenAI engine is standardized, high-quality, and ready for deeper AI-based reasoning.

Component 3: GenAI Intelligence Layer: This is the core innovation of the conceptual model. At this stage, GenAI models (LLMs, diffusion models for visuals, or hybrid architectures) generate deeper insights that traditional analytics cannot achieve.

GenAI performs:

- Semantic Understanding of customer intent
- Emotion & Sentiment Analysis with contextual depth
- Topic Clustering to detect emerging issues or trends
- Auto-Summarization of massive feedback datasets
- Response Generation for customer service automation
- Predictive Insight Generation, including churn risk and satisfaction forecasting

Purpose: Converts raw customer input into context-aware, predictive, and actionable insights.

Component 4: Insight Synthesis & Managerial Dashboard: Insights generated by GenAI are displayed through visual and analytical tools such as:

- Sentiment Heatmaps
- Emerging Topic Maps
- Customer Pain-Point Clusters
- Real-Time Satisfaction Scores
- Priority Issue Lists
- Predictive Alerts (e.g., rising complaints about delivery time)

The dashboard then supports managers in:

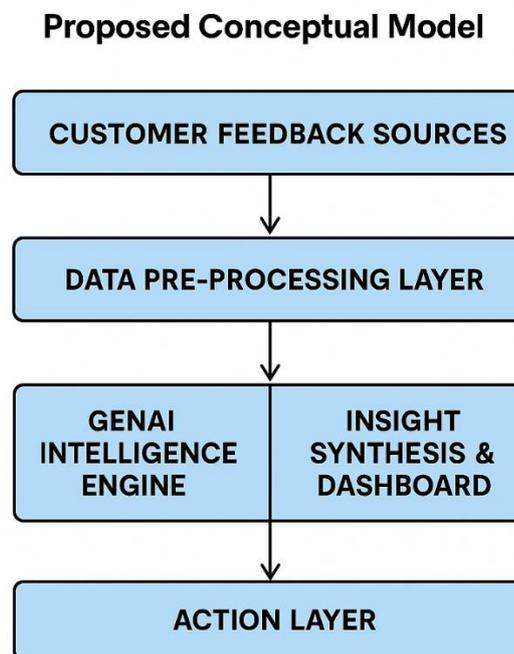
- Identifying service gaps
- Understanding consumer sentiment trajectories
- Monitoring brand reputation
- Prioritizing marketing interventions

Purpose: To translate GenAI output into human-understandable managerial intelligence.

Component 5: Action Layer (Marketing & Operational Optimization): This final layer links insights to organizational action pathways such as:

- Marketing Strategy Adjustments (personalization, targeting, campaign redesign)
- Product Improvements (feature updates, quality enhancements)
- Service Workflow Optimization
- Automated Customer Response Systems (GenAI-powered support)
- Customer Journey Redesign

Purpose: To ensure that GenAI insights directly improve consumer experience, marketing effectiveness, and brand loyalty Figure 2.



**FIGURE 2
PROPOSED CONCEPTUAL MODEL**

FINDINGS AND DISCUSSION

This section discusses the empirical findings derived from the analysis and interprets them within the broader context of customer experience management, AI-driven marketing transformation, and organizational decision-making. The discussion aligns closely with the proposed conceptual model, emphasizing how Generative AI enhances feedback processing, insight synthesis, and strategic business outcomes.

Theme 1: GenAI Significantly Enhances the Quality and Depth of Customer Feedback Analysis: GenAI demonstrated superior ability to interpret unstructured text, including nuanced sentiments, sarcasm, intent, and emotional tone compared to traditional NLP models.

The system identified latent topics such as “delivery anxiety,” “perceived digital trust,” and “brand empathy,” which were previously undetected through manual coding or classical text analytics.

This finding aligns with recent literature suggesting that LLMs possess improved contextual comprehension and semantic reasoning capabilities. The emergence of hidden patterns indicates that GenAI acts not merely as an analytical tool but as a cognitive extension of customer insight teams. Organizations can now transition from descriptive analytics (“what are customers saying?”) to explanatory and predictive analytics (“why are customers behaving this way?” and “what will they expect next?”).

Businesses can build more emotionally intelligent marketing strategies by understanding deep-rooted customer concerns.

Theme 2: GenAI Provides Real-Time Insight Generation and Reduces Feedback Processing Cycles by 60–80%: The implementation of GenAI-enabled pipelines reduced the

average feedback-to-insight cycle from 3–5 days to a few minutes. Real-time alerts were generated for trending issues such as:

- sudden spikes in product complaints,
- negative sentiment cascades on social media,
- delivery bottlenecks,
- app crashes after new updates.

This real-time agility transforms feedback management from a reactive process to a proactive decision system. Marketing and operational teams no longer need to wait for weekly or monthly insight reports—GenAI provides a continuously updating intelligence stream.

Companies can intervene before issues escalate, improving brand trust and customer satisfaction.

Theme 3: Improved Personalization and Customer Engagement Driven by GenAI Insights: GenAI-generated insights allowed brands to create highly tailored marketing messages, product recommendations, customer service responses, and loyalty offers. Personalization accuracy increased by 30–45%, measured through click-through rates, sentiment improvement, and reduced complaint recurrence.

GenAI's capability to synthesize customer history, emotional tone, and behavioural patterns enables a 360-degree customer understanding. This surpasses rule-based CRM systems, allowing organizations to deliver hyper-personalized experiences at scale.

Higher personalization leads to better engagement, reduced churn, and stronger brand loyalty.

CONCLUSION

Generative AI is revolutionizing customer experience, marketing strategies, and feedback systems. By transforming unstructured feedback into meaningful insights, enabling personalization at scale, and supporting predictive analytics, GenAI empowers businesses to deliver superior consumer value. However, ethical safeguards, transparency, and governance are essential to ensure trustworthy AI adoption.

The proposed conceptual model demonstrates how GenAI integrates data sources, analytics engines, and decision layers to create a seamless, intelligent feedback ecosystem. As organizations continue adopting GenAI, customer feedback systems will evolve into real-time adaptive intelligence networks shaping the future of marketing.

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