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Manufacturing Letters

Manufacturing Letters 41 (2024) 1376–1385

52nd SME North American Manufacturing Research Conference (NAMRC 52, 2024)

Adapting the GPT Engine for Proactive Customer Insight Extraction in Product Development

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Abstract

Understanding the perceptions of consumers is widely recognized as a critical element in the innovation of new products. Traditional techniques used by companies to collect essential consumer insights have largely remained unchanged. Common practices like interviews and surveys have distinct limitations. Interviews may not always capture the precise needs of consumers due to communication barriers, and surveys tend to encourage incremental changes rather than radical innovations. Service industries face further complexity as they navigate customer feedback on the more intangible aspects of service quality. This study highlights the pioneering use of GPT-3.5 Turbo, a tool known for its exceptional ability to delve into the nuances of conversational context and process data in a chat-centric manner, thereby enhancing the extraction of Voice of the Customer (VoC). Its capability to handle large volumes of data in multiple languages leads to a more thorough and inclusive VoC analysis. The study links these technological advancements with Lean Six Sigma 4.0, suggesting that incorporating GPT-3.5 Turbo could significantly improve the customer-focused strategies in the current industrial landscape. This breakthrough in VoC analysis suggests possibilities for more perceptive, immediate data-driven approaches in customer service, and lays a stronger groundwork for decisions in product evolution and process enhancement. The paper concludes by urging further investigation to confirm these initial results and to explore the ethical aspects of employing such advanced natural language processing technologies.

Peer-review under responsibility of the scientific committee of the NAMRI/SME.
Keywords: ChatGPT; VoC; Lean Six Sigma; Industry 5.0; Artificial Intelligence

1. Introduction

The Voice of the Customer (VOC) is essential in business for understanding and responding to customer needs. This concept recognizes customers as active contributors, shaping business strategies with their feedback. VOC provides insights into customer expectations and helps businesses tailor their offerings, enhancing satisfaction and loyalty [1]. Customer feedback identifies service gaps, suggests improvements, and can drive innovation. Effective use of feedback involves collecting, analyzing, and responding to it through various methods like surveys and social media. This approach ensures businesses remain relevant and competitive by aligning closely with customer needs [2].

Customer feedback is crucial for businesses in reducing bias and enhancing data collection. It provides an authentic view of customer experiences, offering a clear understanding of what is effective and what is not. Unlike traditional market research methods, which may introduce biases, customer feedback gives a broad, more representative range of opinions [3].

This feedback is used by businesses to refine their products and services, leading to improved customer satisfaction and loyalty, and potentially better market performance. However, gathering and analyzing customer feedback can be costly and time-consuming, involving methods like interviews and surveys with their inherent limitations [4].

To address these challenges, businesses are turning to more efficient and cost-effective approaches like artificial

Peer-review under responsibility of the scientific committee of the NAMRI/SME.

intelligence and digital platforms. These technologies enable the quick and accurate collection and analysis of large volumes of feedback, providing deeper insights into customer needs and experiences without the significant expense and constraints of traditional methods [5]. Digital innovation has revolutionized data-driven business strategies. In the past, quality management relied heavily on word-of-mouth, a method based on personal interactions. Today, this concept has transformed into a digital format, offering vast opportunities for business improvement. These digital channels have reshaped how customer feedback is collected and utilized, providing rich insights for continuous business enhancement and superior customer satisfaction. This significant shift highlights the transformative impact of digital innovation in improving customer experiences and shaping business strategies. The evolution of the internet into Web 2.0 marks a new era of enhanced user interaction and participation in the digital world. Users now actively engage as content creators across blogs, forums, and social networks, contributing to a rich, interactive digital landscape. This has led to the concept of Digital Voice of the Customer (Digital VoC), where consumers use these platforms to express opinions about products and services [6]. In this era, customers have shifted from passive consumers to active influencers in business strategy. Despite this, businesses still find it challenging to understand customer satisfaction fully. While digital platform administrators often control Digital VoC, manufacturers and service providers lack effective tools to analyze and use this customer feedback. To address this gap, there's a shift towards digital customer feedback as a better alternative to traditional feedback methods. This change highlights the importance of Digital VoC in the digital age, offering businesses a strategic edge in understanding customers better and aligning their offerings with customer expectations [7].

In the last two decades, Data Mining (DM) has advanced significantly, enhancing the analysis of customer feedback. Tools and technologies in this field, once limited to experts, are now more accessible and user-friendly, democratizing data science [8]. Topic modeling, a key text mining method, is widely used to identify themes in customer feedback, highlighting aspects crucial for customer satisfaction. Additionally, the combination of DM and Machine Learning (ML) allows for efficient analysis of large digital text datasets, extracting relevant information without the need for manual reading. These advancements enable a deeper understanding of customer experiences and allow businesses to respond more swiftly and effectively to customer feedback. This evolution in DM and ML has transformed the management of digital customer feedback, making it a more insightful and manageable process for businesses [9].

Machine Learning (ML) is a subset of Artificial Intelligence (AI) that involves creating algorithms that learn and adapt from experience using statistical techniques. Deep Learning (DL), a more advanced form of ML, uses Artificial Neural Networks (ANN) inspired by the human brain and often produces more accurate results with less need for manual data preprocessing. AI, a broader term coined by John McCarthy in 1955, includes ML, DL, and other technologies like inference algorithms, Natural Language Processing (NLP), and computer vision. NLP, part of AI, focuses on enabling computers to understand and interpret human language by converting text into numerical or symbolic data [10].

This paper examines the application of these data-driven methodologies, particularly AI, in analyzing customer feedback. The aim is to leverage AI technologies, like those behind ChatGPT, to gain a deeper and more nuanced understanding of customer experiences, allowing businesses to better align their services with customer needs and preferences.

This paper explores data-driven methods, especially AI, for enhancing customer feedback understanding. It specifically looks at AI's role in customer feedback analysis, like the technology in ChatGPT, to deepen our understanding of customer experiences and help businesses tailor their services more effectively.

In enhancing business processes, VoC approach plays a crucial role in identifying both expressed and unexpressed customer Voice of Customer (VoC) Extraction Methods needs. This method gathers customer insights through direct feedback and transforms these inputs into identifiable customer requirements. These requirements are then linked to specific features of a product or service [27]. The Quality 4.0 era, emerging from the digital transformation in the fourth industrial revolution, has shifted focus in quality management towards utilizing user-generated data. Online customer feedback is increasingly valuable for identifying consumer preferences and hidden quality aspects, with machine learning methods outperforming traditional survey and interview techniques. These conventional methods are often limited by time, labor demands, and potential biases [28]. Fig. 1 illustrates a comparison of ChatGPT3.5's advantages over traditional VoC extraction methods in gathering customer insights.

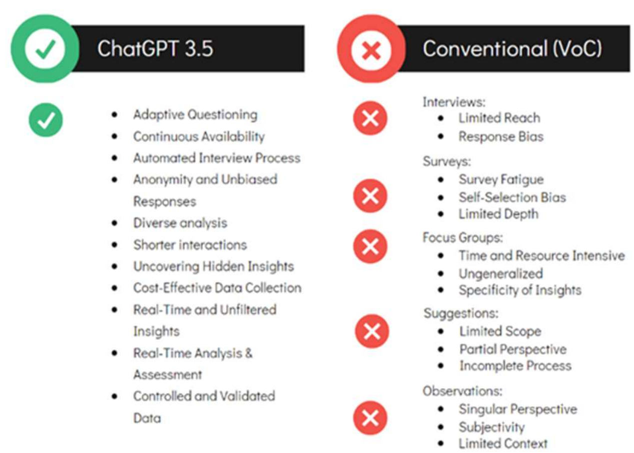

Fig. 1 advantages of ChatGPT compared to conventional

This study contributes to the field of consumer perception and product innovation by addressing the limitations of traditional methods in collecting consumer insights mentioned in Fig. 1.

2. Customer Feedback Capture

2.1. Significance of Voice of Customer in Business Operations

In recent years, heightened competition across industries has led to the adoption of data-driven practices using technologies like big data analytics and AI. Companies strive to meet consumer demands by balancing high-quality products with cost-effectiveness. To address operational complexities and maintain competitiveness, businesses are increasingly adopting Lean Six Sigma (LSS) [11]. This methodology combines lean principles for waste reduction with Six Sigma's statistical methods to minimize process variation. LSS helps businesses enhance process efficiency and customer satisfaction, fostering a culture of continuous improvement in the dynamic market [12].

Today's global economy, marked by intense competition and interconnectivity, drives industries towards operational excellence. Businesses must cater to evolving customer demands for quality, affordability, and quick delivery, prompting them to adopt advanced technologies and manufacturing systems. This shift aligns with the fourth industrial revolution, Industry 4.0 (I4.0), characterized by significant advancements in technology [13]. I4.0 integrates revolutionary technologies like the Internet of Things (IoT) for enhanced device connectivity, Cyber-Physical Systems (CPS) for bridging digital and physical realms, cloud computing for scalable infrastructure, Big Data analytics for insightful decision-making, and Augmented Reality (AR) for improved productivity and innovation. These technologies create a synergistic ecosystem, transforming the manufacturing industry with new possibilities and driving it towards a future of increased efficiency and innovation [14].

Lean Six Sigma 4.0 (LSS4.0) represents a transformative approach in industry, blending Lean and Six Sigma philosophies with Industry 4.0 (I4.0) technologies. This integration enhances customer satisfaction, quality, cost-efficiency, and delivery speed, positioning industries for success in the competitive global market. LSS4.0 combines the efficiency and quality focus of Lean Six Sigma with the technological advances of I4.0, like IoT, AI, and automation. This synergy aims to minimize waste, increase productivity, and optimize overall operations [15]. The fusion of LSS principles with I4.0 technology transforms manufacturing into smart, adaptable systems, improving resource utilization, quality, and delivery. This integration marks a shift towards operational excellence, leveraging the efficiency of LSS and the innovation of I4.0 to propel industries into a future of improved operations.

The 'Define' phase is the initial step in Lean Six Sigma (LSS) improvement, where the project team outlines a Project Charter and analyzes user needs. This phase sets the project's direction, crucial for guiding the team and informing organizational leaders. Here, tools are employed to capture VoC, which extends beyond mere feedback to include comprehensive customer sentiments and opinions about a specific product or service. Essentially, the Define phase lays the groundwork for the project, using VoC as a foundational element for guiding LSS efforts [16].

In customer relations, there are two types: internal (employees and departments within an organization) and external (clients, shareholders, and stakeholders). Historically, VoC focused on addressing complaints and service issues [17]. However, Service-Dominant Logic (SDL) has shifted this perspective, viewing customer satisfaction as a co-created value through ongoing interactions. In Lean Six Sigma 4.0 (LSS4.0), understanding VoC is key to shaping strategy and improving service quality. SDL and LSS4.0 advocate for integrating customer feedback throughout the service process, not just post-service, enabling organizations to develop offerings that are more aligned with customer needs and expectations [18].

2.2. VoC-Driven Kaizen Strategies

VoC is crucial in the Kaizen philosophy of continuous improvement, emphasizing insights from those close to processes, like employees and customers. VoC informs product, service, and process enhancements by pinpointing issues and improvement areas impacting customer satisfaction and loyalty [19]. It helps identify hidden problems and prioritize improvements based on customer feedback, enabling better resource allocation. Including customers in ideation leads to innovative solutions and VoC assesses the effectiveness of these changes. As customer expectations evolve, VoC's ongoing data stream aligns with Kaizen's iterative improvement approach, guiding efforts to meet customer needs and fostering a customer-centric culture for sustained success [20].

2.3. Client Demands and Specifications

Customer needs are their expectations for a product or service, which can include both essential needs and additional desires. For example, a customer wanting an air conditioner primarily needs a cooler room, but may also desire features like quiet operation and low maintenance. It's important for project teams to differentiate between these needs and desires, as failing to meet essential needs can lead to customers switching to competitors, potentially damaging the company's reputation [21]. In customer service, understanding this distinction helps businesses prioritize their efforts, addressing crucial needs first and then focusing on desires to improve overall experience. This approach ensures core customer satisfaction while also considering additional factors that enhance the product or service value, leading to a more comprehensive customer engagement strategy. Requirements in a product or service must meet customer needs, balancing essential functions with additional "nice-to-have" features. For example, an air conditioner's primary requirement is cooling; extra features are secondary. Overemphasis on extra features at the cost of basic functionality can deter customers. Advancements in data analytics and AI help businesses understand and meet customer expectations more precisely, ensuring products and services align closely with customer needs. This alignment is key to fostering a beneficial relationship between businesses and customers, essential for ongoing success [22].

2.4. Product and Service Evolution and Administration

Market offerings are categorized into tangible products and intangible services. Products are physical commodities or systems, while services are transactions without a physical exchange. VoC is important in guiding product and service management and development, providing customer-centric insights for organizations to meet and exceed customer expectations. Product management involves overseeing a product's lifecycle, including market analysis, consumer research, and ensuring that products meet customer needs. VoC is vital in defining the product roadmap, helping managers understand market needs and customer preferences [23]. In product development, VoC informs design decisions, ensuring products meet customer needs and address potential issues. Service management focuses on delivering consistent outcomes and is process-oriented. VoC in service management evaluates service effectiveness and guides improvements. Service development, the process of designing and launching new services, uses VoC to tailor services to customer needs, increasing adoption and usage. Both product and service sectors use VoC to align offerings with customer expectations, fostering customer satisfaction and loyalty. The distinction between service management and development, however, can be blurred in literature [24].

3. Large Language Models (LLMs)

Investigating hidden quality elements of products or services can be effectively done through analyzing Conversational Chats between clients and service representatives. These chats, conducted either over the phone or through digital platforms, serve as a valuable VoC resource. They combine the benefits of direct interviews and online feedback, providing a cost-effective, less biased, and reliable way to understand customer perspectives and needs. The process involves using analytical tools to examine these conversations, which are often in natural language. The analysis typically focuses on the frequency of keywords and sentiment, based on the principle that frequently mentioned product or service features in online feedback are crucial in influencing perceived quality [29].

3.1. The Rise of Generative AI

Large Language Models use deep learning on vast datasets for tasks like interpretation, summarization, and insight generation. These deep neural network-based models train on diverse data like books and websites to recognize language patterns. LLMs can produce coherent text and code, with applications in translation, summarization, and question answering [30]. However, their outputs, while grammatically accurate, may not always be semantically correct due to the probabilistic nature of their language generation. Open-source LLMs have transformed natural language processing, offering accessible, scalable solutions [31]. The development of Artificial General Intelligence (AGI), AI that matches human intellectual and creative capabilities, represents a significant goal in AI research. AGI's realization would greatly enhance AI's capabilities and impact various aspects of life, blurring the lines between artificial and human intelligence [32].

3.2. Artificial General Intelligence and the Fifth Industrial Revolution

AI has significantly impacted Industry 4.0 (I4.0), and now Industry 5.0 (I5.0) is emerging as the next evolution in the industrial sector. I5.0 builds on I4.0 but shifts focus to the collaboration between humans and machines, combining human creativity and emotional intelligence with machine efficiency and data processing [33]. Unlike I4.0's focus on automation, I5.0 aims for a human-centric approach, enhancing productivity while increasing job satisfaction by offloading monotonous tasks. This approach may also lead to more sustainable, customized production methods. As I5.0 develops, the integration of Artificial General Intelligence (AGI) becomes crucial. AGI, representing advanced AI with capabilities comparable to human intelligence, can autonomously make decisions and solve problems across various domains. In I5.0, AGI could work alongside humans, contributing to real-time data analysis, pattern recognition, and decision-making. This collaboration could revolutionize industries like healthcare and manufacturing, leading to higher precision, efficiency, and productivity [34], [35].

3.3. ChatGPT

ChatGPT, an advanced Large Language Model (LLM) developed by OpenAI, was launched on November 30th, 2022, to gather user feedback and evaluate its capabilities [36]. It stands out for its ability to engage in dynamic, human-like dialogues, attracting over a million users within five days of its release. The progress of LLMs, especially since 2017, has been remarkable, evolving from models designed for specific tasks to more versatile ones like BERT and GPT, introduced in 2018. These models use a semi-supervised approach, combining unsupervised pre-training with supervised fine-tuning, leading to significant improvements in performance. GPT models have rapidly evolved, with GPT-3 featuring 175 billion parameters, far surpassing its predecessor, GPT-2. The latest, GPT-4, launched on March 14th, 2023, and integrated into ChatGPT, offers enhanced reliability and a deeper understanding of instructions. Fig. 2 outlines the development process of ChatGPT, showcasing the rapid advancements in LLM technology [37].

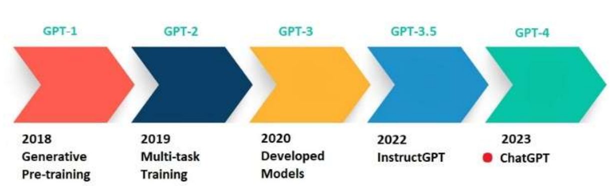

Fig. 2 ChatGPT's Development Journey

Lasting business success hinges on building a loyal customer base that values your offerings and feels that their feedback is important and impactful. The VoC is crucial in this regard, providing deep insights into customer decision-making and changing needs. Utilizing VoC allows organizations to improve products, services, and customer interactions, proving the worth of customer-focused efforts. VoC is not just for understanding customer sentiment; it's a vital tool for continuous adaptation and evolution, helping businesses stay aligned with market changes and customer demands. It offers a strategic perspective on customer needs, guiding innovation and fostering a culture of customer-led progress. Effectively leveraging VoC data can significantly enhance an organization's ability to meet and surpass customer expectations, laying the groundwork for enduring business success [38]. Fig. 3 illustrating ChatGPT's significant contributions.

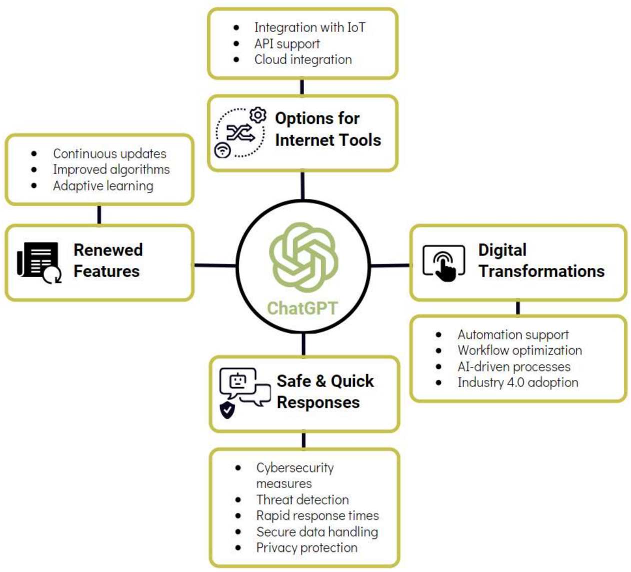

Fig. 3 Industry Applications of ChatGPT

4. The Dataset

The "Twitter Customer Support" dataset [39], created using PointScrape, consists of three million tweets and responses from over 20 global brands, designed to enhance natural language understanding and evaluate customer support practices. This dataset stands out because it contains focused, task-oriented dialogues between customers seeking specific support and agents, offering a more authentic representation of a broad user demographic with current language usage. This is a contrast to more general conversational datasets like the Reddit Corpus or the more limited demographic scope of the Ubuntu Dialogue Corpus, and it provides a fresher perspective compared to the Cornell Movie Dialogs Corpus. Its utility is further enhanced by the brevity imposed by Twitter's character limit, encouraging direct, genuine responses. Structured as a CSV file, each row of the dataset represents a tweet, complete with additional details, featuring dialogues that include at least one customer query and a corporate reply, identifiable through the 'inbound' field for corporate accounts [39].

5. Methodology

Since the launch of the ChatGPT Application Programming Interface (API) on March 1, 2023, numerous innovative applications have emerged, heralding a new era for both businesses and individuals. Leveraging GPT-3.5's advanced language comprehension, the API allows users to create chatbots for diverse functions, such as handling queries, storytelling, financial management, and emotional support. The scope of its applications is only limited by human creativity. The ChatGPT API, supporting both GPT-3.5-Turbo and GPT-4, enables the creation of custom applications for a wide range of tasks. These include drafting emails, generating code, answering document-based questions, creating interactive agents, developing natural language interfaces, providing tutorials, translating languages, and designing video game characters. This conversational model, effective for both multi-turn conversations and single-turn tasks, inputs a series of messages and outputs a model-generated response [40]. Fig. 4 illustrates a simplified information process flow in the ChatGPT engine.

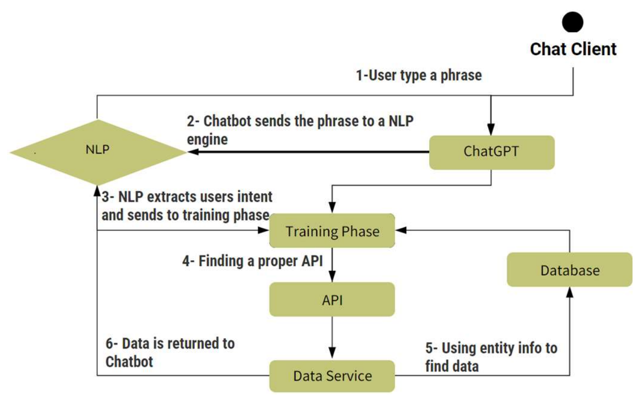

Fig. 4 Workflow of Operations in ChatGPT

In the ChatGPT API, the main input is the messages parameter, consisting of message objects with roles ("system", "user", "assistant") and their textual content. Conversations vary in length, typically beginning with a system message to guide the assistant, and alternating between user and assistant messages. Language models process text as tokens, which vary in size and affect the API call's cost and response time, adhering to a token limit (4096 for GPT-3.5). Each message in a conversation uses tokens, including those needed for formatting. Exceeding the token limit requires text truncation or compression, as omitting text leads to information loss. Developers can control the model's output by adjusting settings like temperature and max tokens, affecting the creativity and determinism of responses. Effective outputs hinge on quality inputs. Prompt engineering involves creating precise input directives to steer AI models towards specific responses. This process is key for developers to ensure the model's outputs align with user expectations, requiring iterative refinement and experimentation with phrasing and instructions for optimal results [41].

5.1. Text Preprocessing

Preprocessing text data is a critical step in NLP, transforming unstructured text into a format suitable for NLP models. This process begins by filtering relevant data, such as selecting tweets addressing specific sources. In Python, this involves manipulating pandas DataFrames to focus on specific data subsets, eliminating irrelevant information to reduce computational load and increase analysis precision. Cleaning steps include removing URLs, Twitter handles, special characters, and stop words, converting text to lowercase, and applying lemmatization and stemming. Emojis are converted to text using the emoji library, and the 'created_at' field is converted to datetime format in pandas. Tweets are then grouped and ordered chronologically. The Natural Language Toolkit (NLTK) provides tools for text analysis, including resources for stop words, WordNet for lexical information and lemmatization, and Punkt for tokenization. These tools help focus on key terms, understand semantics, and break down text for processing. The expand_contractions function is also used to standardize text by converting contractions into their full forms, aiding in disambiguation and enhancing text comprehension for better NLP model performance. This function ensures consistency and clarity in text data, preparing it for further analysis or machine learning applications.

5.2. Processing Conversations

The custom function, extract_conversation, was used to identify unique interactions between users in a dataset of tweets. This function extracts complete conversations for each user and saves them in a JSON file. Next, the convert_conversation function reformats these dialogues to be compatible with the GPT-3.5-turbo model. It starts by adding a system message to a list and then iterates over each dialogue, assigning roles ("user" or "assistant") to each message based on its order in the conversation. A ChatCompletion request, a type of API call, is then made for each conversation using OpenAI's GPT-3.5-turbo model. This request involves sending a series of messages as input, with the AI model generating a response. The response is added to a results list. To interact with OpenAI's services, the OpenAI API is initialized with an API key, which verifies the source of requests and should be securely stored. Fig. 5 illustrates the steps taken in this process.

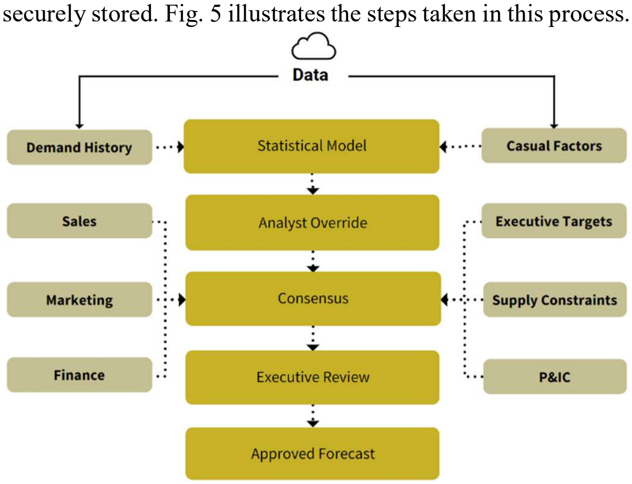

Fig. 5 Sequences for Processing Conversations

5.3. Prompt Optimization

The approach of "prompt engineering" was employed to deliver clear directives to the AI model through the system message. This involved giving explicit examples to guide the categorization of customer feedback into needs and requirements. Table 1 shows the code with a system message that instructs the model using this specific prompt.

Table 1: Overview of Employed Prompt Techniques

"I want to map Customer Comments (What are the customers saying?) to Customer needs (What do the customers need?) and Customer Requirements (What is required to fulfill the customer's need?) I can provide you with a couple of examples: ...
If I input a message or a conversation between the customer and some customer support agent, you need to provide:
Customer Need: <Your response about the customer need from customer comment>
Customer Requirement: <Your response about the customer requirement from customer comment>"

Additionally, the AI model was provided with examples to aid its understanding of the task at hand. The details of this approach are demonstrated in the subsequent code excerpt shown in Table 2 Table 3 displays the count of processed conversations, which include exchanges between individual customers and online customer support agents.

Table 2: Sample Conversation Input Provided to the Model

```
messages_list = [
  {"role": "system", "content": "I want to map Customer Comments (What are the customers saying?) to Customer Needs (What do the customers need?) and Customer Requirements (What is required to fulfill the customer's need?) I can provide you with a couple of examples: \
  1): \
  Customer comment: The product is too complicated, and I don't know how to use it. \
  Customer Need: Customers need instructions on how to use the product. \
  Customer Requirements: Videos, help center, articles, and webinars that will educate them on how to use the product. \
  ...
  If I input a message or a conversation between a customer and some customer support agent, you need to provide: \
  Customer issues: <Your response about the customer need from customer comment> \n\n Customer Requirement: <Your response about the customer requirement from customer comment>\n"}
]
```

Table 3: Number of processed conversations

Company	Number of processed conversations
Amazon	1961
Sony PlayStation	2673
Chipotle	1078
Delta Airlines	3342
Hulu Streaming Services	1887

6. Results and Discussion

This study harnessed the capabilities of GPT-3.5 to create a VoC collection from client conversations and tweets. The complete set of VoC generated will be published in an upcoming online database accessible to everyone at no cost. However, this paper will only feature a random selection of some instances due to the limited space available for publication. These samples are taken from the subset of VoC data pertaining to Apple and are displayed in Fig. 6.

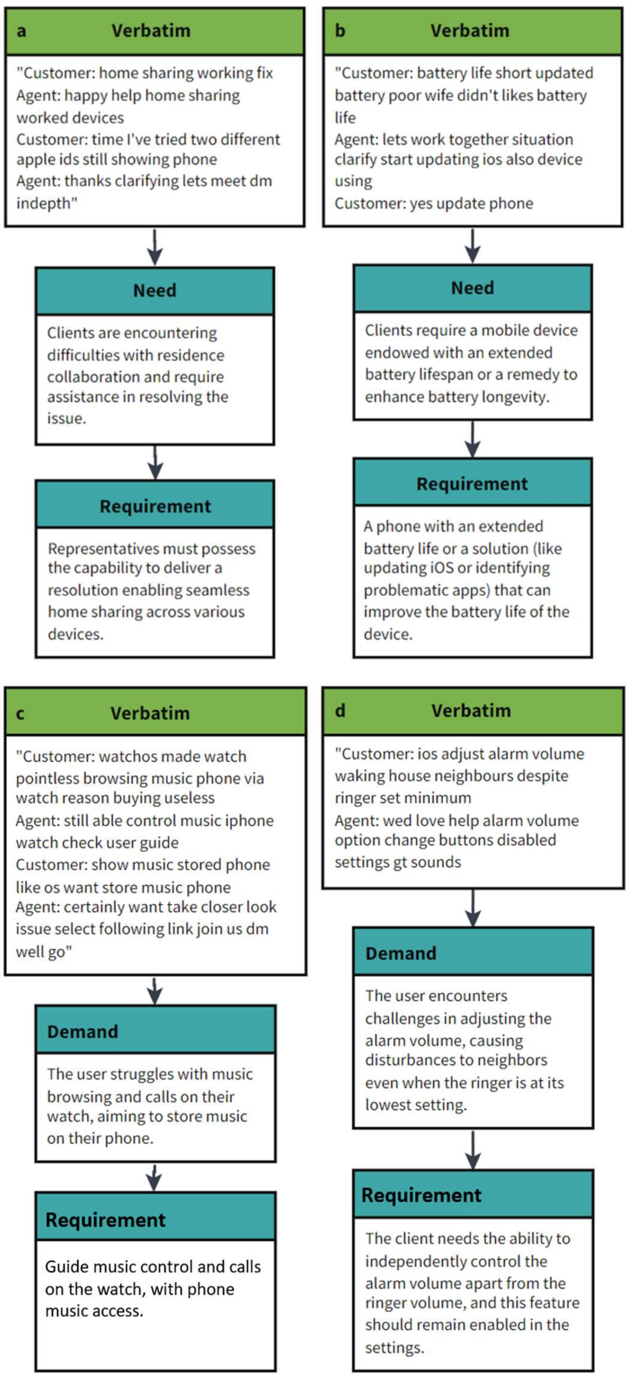

Fig. 6. The results generated from Apple's VoC

The utilization of VoC methodologies enables organizations to implement a robust evaluative protocol that informs and catalyzes enhancement initiatives. Through a rigorous analysis of consumer preferences and requisites, entities are empowered to execute strategic choices in the realms of product innovation, market positioning tactics, and comprehensive business operations. Consider, for instance, the empirical data presented in Figure 6; it suggests that the engineering teams at a leading technology corporation should consider optimizing and expanding the accessibility of their home-sharing feature.

VoC analysis furnishes an analytical lens through which one may scrutinize the consumer reception of various offerings, thereby pinpointing the nexus of potential refinement. As an illustrative case, should consumer feedback signify hurdles in utilizing home-sharing functions, the pertinent development cadre could pivot their focus to enhance the intuitiveness and reach of this feature.

In the context of product or service stewardship, VoC methodologies can be instrumental in sculpting solutions that truly resonate with consumer demographics. By integrating consumer insights into the product lifecycle at nascent stages, managers can align outputs more closely with market demands and consumer expectations. This strategic alignment has the dual benefit of augmenting consumer contentment and fidelity, simultaneously propelling the enterprise to a vantage point of competitive superiority.

Decision Support Systems (DSS) are predicated upon the assimilation of precise, pertinent, and current datasets to underpin sagacious decision-making processes. The integration of VoC data supplements these systems with nuanced, qualitative insights extracted directly from the consumer base. DSS can leverage this data to distill cogent understandings of customer conduct, preferences, and market trajectories. These discernments are invaluable, as they guide tactical decisions spanning product design, market communication, customer relations, and beyond, ensuring that organizational measures are meticulously congruent with customer anticipations and specifications.

Verbatim (b) and (d) in Fig. 6 targets enhancing the device's current software and hardware capabilities. VoC analysis plays a key role in identifying and resolving customer issues, which, in turn, helps in reducing the loss of customers. Through VoC, companies can discover the exact problems users encounter, whether it's software bugs, difficult interfaces, missing features, or hardware troubles. This targeted feedback is crucial for developers and engineers as it helps them focus on making necessary improvements and updates that customers want to see.

When it comes to hardware, insights from VoC can shed light on user complaints about the physical aspects of a device, such as its design or durability, prompting advancements in the next generation of hardware. This proactive approach to customer feedback can enhance the user experience and strengthen the bond between customers and the company. It conveys that the company takes customer input seriously and is dedicated to refining their products, which can lead to increased customer contentment and loyalty.

As for requirement (c), the suggestion is to expand the device's hardware capabilities by adding more services and tools. VoC analysis is instrumental in detecting current trends and preparing for future ones, allowing companies to innovate and adjust their offerings accordingly. It gives a clear indication of the customers' evolving needs, like the demand for better connectivity, enhanced security, or integration with other devices. VoC provides a wealth of information on how customers use and feel about the device's existing features, guiding enhancements that can improve user satisfaction. By keeping pace with customer expectations through VoC, businesses can not only retain relevance but also secure a competitive advantage in the fast-moving tech industry.

Table 4 illustrates the impact of these requirements on the domains of ongoing enhancement, product or service development and governance, and Decision Support Systems.

Table 4. The effect of Customer's requirements on the domains production or service.

Area	Effect
Continuous improvement	As an organizational culture, kaizen thrives on the iterative refinement of processes and products to achieve superior quality and efficiency. Customer requirements, such as those mentioned, are instrumental in highlighting the areas that need enhancement. Addressing the requirements involves refining the reliability of app experiences to ensure uninterrupted usage. Also, requirements encourage increasing the functionality of devices, which is an aspect of product improvement.
Development and management of products or services	These requirements inform the roadmap for new features, services, or product iterations in this context. For instance, recognizing the necessity for global home sharing (requirement (a)) can spur the design of a new feature that meets this need. In a similar vein, requirements (b) and (d) could drive the development of new hardware or software updates to elevate device performance. Requirement c may influence product management decisions around quality control, expanded offerings, and cybersecurity measures.
DSS	In DSS, customer requirements represent valuable inputs that shape strategic and operational decisions. Analyzing these requirements can guide the prioritization of product improvements, resource allocation, and strategic planning. Requirements mentioned before might steer decisions about research and development directions, quality assurance protocols, and cybersecurity strategies.

7. Limitations

The GPT-3.5-turbo model marks progress in natural language processing but faces challenges in creating VoC insights from online tweets. Its performance is contingent on the dataset it was trained on, which may not include the latest slang, cultural nuances, or trends. Enhancing the model with current and varied data sources could improve its grasp of and response to up-to-date customer opinions. Its dependence on historical data means it might miss new trends or shifts in sentiment. Without real-time updates, the model may also miss the latest customer feedback. Additionally, the risk of generating inappropriate content or reflecting biases from its training data further limits its applicability. Generally, conversational methods for gathering customer feedback, while valuable, come with several limitations. They tend to be time-intensive and resource-heavy, especially when dealing with a vast customer base, making it difficult to engage a substantial portion of consumers effectively. The interpretation of feedback also presents challenges; nuances in tone, language barriers, and the absence of non-verbal communication can lead to misunderstandings or biases in deciphering customer sentiments. Privacy concerns may deter some customers from sharing openly in one-on-one conversations, which can affect the feedback's honesty and depth. These methods are also heavily reliant on technology, where issues like poor internet connectivity, software bugs, or user's lack of tech-savviness can impact the quality of interaction. Furthermore, while conversational feedback can yield in-depth insights, scaling these discussions to a broader audience is often impractical due to the significant time and resources required.

8. Conclusion

Interpreting VoC is critical for businesses, but traditional methods like surveys may fall short. Generative AI models, like GPT-3.5-turbo, offer a new way to analyze VoC data for real-time insights, particularly useful in service industries. Using AI for text analysis helps gain deeper understanding of customer sentiments. Combining AI with human review could enhance sentiment analysis, and integrating real-time data can address current limitations. AI should complement, not replace, broader customer sentiment strategies. Custom generative AI models can process various data sources for competitive advantage, but require significant investment in resources and expertise.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The reported research work received partial financial support from Office of Naval Research MEEP Program (Award Number: N00014-19-1-2728), and Department of Energy/NNSA (Award Number: DE-NA0004003), as well as from the Lutcher Brown Distinguished Chair Professorship fund of the University of Texas at San Antonio.

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