Proceedings of the 10th North American International Conference on Industrial Engineering and Operations Management, Orlando, Florida, USA, June 17-19, 2025

Proceedings of the International Conference on Industrial Engineering and Operations Management

Publisher: IEOM Society International, USA DOI: 10.46254/NA10.20250258
Published: June 17, 2025

Integration of Artificial Intelligence and Kano Model: A Systematic Literature Review

Mehrnoosh Saeyan and Ahmad Elshennawy
Department of Industrial Engineering & Management Systems
University of Central Florida
Orlando, FL, USA
Mehrnoosh.saeyan@ucf.edu, Ahmad.Elshennawy@ucf.edu

Elizabeth Cudney
John E. Simon School of Business
Maryville University
St. Louis, Missouri, USA
ecudney@maryville.edu

Abstract

Incorporating Artificial Intelligence (AI) into the Kano model presents significant possibilities for improving quality management, increasing customer satisfaction evaluations, and refining product or service development plans. This systematic literature review explores the current research on the integration of AI with the Kano model, highlighting significant trends, advantages, and obstacles. The data analytics capabilities of AI allow for the automation and enhancement of Kano's feature classification, hence enabling more accurate identification of customer preferences and dynamic feedback mechanisms. This study classifies the reviewed publications into two groups: those leveraging textual data (e.g., customer evaluations) and those adopting alternative analytical tools to augment the Kano model. Research demonstrates that AI-driven methodologies enhance the efficiency and precision of Kano's framework, providing real-time insights and predictive functionalities. However, problems including quality of data, questionnaire biases, and integration issues are acknowledged, underscoring the necessity for additional study to mitigate these limitations and fully realize the potential of this integrated method.

Keywords
Kano Model, Artificial Intelligence, Customer Satisfaction, Online Reviews

1. Introduction
In today's competitive global marketplace, customer satisfaction is a critical non-financial driver of business success (Hallencreutz & Parmler 2021). As consumer expectations continue to evolve, organizations are increasingly adopting sophisticated tools and models to understand and respond to these changing needs, to deliver exceptional value (Weinstein 2020). The Kano model, developed by Professor Noriaki Kano, is a well-established framework for understanding customer preferences by categorizing and prioritizing product features into five types, including Must-be, One-Dimensional, Attractive, Indifferent, and Reverse. (Kano et al. 1984; Yang 2024; Zhenyu & Kongjit 2024). The simplicity and practicality of the Kano model have established it as a fundamental framework across diverse industries, including manufacturing, healthcare, and different services (Shahin et al. 2013). However, the model's traditional application relies heavily on manual data collection and analysis, often through survey techniques, which may not fully capture modern consumer markets' complexity and dynamic nature (Jin et al. 2022).
Artificial intelligence (AI) has changed how businesses collect and analyze data, making it possible to make faster and more accurate decisions. With tools like machine learning and predictive analytics, companies are now better

equipped to forecast demand, streamline supply chains, and strengthen customer relationships. Most importantly, AI allows organizations to respond quickly to changing customer needs by providing real-time, data-driven insights (Barzizza et al. 2023; Haleem et al. 2022; Johnson et al. 2021). The integration of established models like the Kano framework with AI has the potential to automate and refine how organizations assess customer needs and expectations, which leads to more responsive and efficient quality management and customer satisfaction practices (Al Rabaiei et al. 2021). Moreover, utilizing AI's predictive capabilities helps companies identify emerging trends in consumer preferences and preemptively adjust their offerings to maintain a competitive edge (Peruchini et al. 2024).

Several studies have explored AI's impact on customer satisfaction and product development. For example, AI can automate the evaluation of product performance, service quality, and customer input, which enables appropriate modifications to product design and features, ultimately increasing customer satisfaction levels (Quan et al. 2023). There are many pros in using AI-driven analytics, such as the real-time feedback loops, which allow companies to swiftly adapt their strategies based on evolving customer needs and sentiments (Ledro et al. 2022). Additionally, utilizing data mining methodologies along with the Kano model improves the ability to pinpoint product or service attributes that drive customer satisfaction, consequently improving organizational performance and mitigating the risk of wasting resources on unnecessary features (Al Rabaiei et al. 2021).

Given the rapid evolution of consumer markets and the increasing availability of AI technologies, it is crucial to revisit how traditional customer satisfaction tools can be adapted to this changing environment (Ingaldi & Ulewicz 2019). Companies that utilize the integration of AI with the Kano model may improve their ability to respond to shifting customer demands and gain a competitive advantage through more agile and precise quality management practices (Shi et al. 2023). Moreover, as consumer behavior and needs become increasingly complex, integrating AI technologies can significantly improve the understanding and prediction of customer needs and expectations (Peruchini et al. 2024). Despite the individual strengths of the Kano model and artificial intelligence (AI), limited research has explored their integration to optimize quality management practices. While AI has been extensively applied in areas such as customer relationship management and business analytics, its combination with established frameworks like the Kano model remains underdeveloped. This represents a promising research frontier, as merging AI's data processing capabilities with the Kano model's structured approach to customer satisfaction could significantly enhance how organizations identify, prioritize, and respond to customer needs across various industries (Al Rabaiei et al. 2021; Zhang et al. 2023). This gap in the literature reflects a missed opportunity to cover the ability to utilize AI in empowering practical applications of the traditional Kano model.

1.1 Objectives

This literature review examines how AI's capabilities can enhance the functionality of the Kano model by reviewing existing research, addressing integration challenges, and offering insights to guide scholars in their future studies in the field of quality management strategies.

By addressing the current gap in the literature, we are aiming to answer our research questions:

How does integrating AI's predictive and data processing capabilities into the Kano model enhance the identification of customer preferences and improve quality management processes across various industries?

What are the primary obstacles and limitations in combining AI technologies with the traditional Kano model?

2. Methodology

A systematic literature review method is applied to ensure transparency and reproducibility in investigating the combination of Artificial Intelligence (AI) with the Kano model, in recent years, from 2019 to late 2024. The structure of this systematic literature review is adopted from Tranfield et al. (2003) and contains planning, implementing, and presenting the findings of the review. This study also employed the "Preferred Reporting Items for Systematic Reviews and Meta-Analyses" (PRISMA) protocol to conduct a thorough systematic literature review.

2.1 Planning the Review

This paper explores and reviews published literature that used AI to improve the traditional Kano model and identifies future opportunities for developing the existing studies. This literature review focuses on studies published between 2019 and October 2024. This period provides us with an updated overview of the knowledge and effort in this field of study. The databases that are used in this literature review include Web of Science, Compendex (Via Engineering Village), and Google Scholar, and articles are selected from peer-reviewed journals. The main contributions of each study are explained in the narrative, while Tables 1 and 2 highlight key techniques, application focus, strengths, and limitations. It should be mentioned that the listed limitations are a combination of points explicitly mentioned in the study and others that are interpreted based on the methodology and discussion provided by the authors.

2.2 Implementing the review

The Web of Science database was searched by the 'Topic' field, while the Compendex database search was conducted within the 'Subjects/Titles/Abstracts' fields. The following keywords were applied in both databases: ("Artificial Intelligence" OR "AI") AND ("Kano"), and ("Artificial Intelligence" OR "AI") AND ("Kano model"), and a total number of 89 articles were found. In addition, the first 10 pages of Google Scholar were explored, and 11 articles were identified. All together, 100 articles were initially retrieved across all sources. After applying limitations such as publication year and English language, the number was reduced to 75. These articles were evaluated based on the title, abstract, keywords, and the inclusion/exclusion criteria outlined in the protocol. As a result, 19 articles were selected for performing a comprehensive review. The selected papers integrate AI with the Kano model and contribute to the further development of the traditional Kano framework. Figure 1 and 2 represents the PRISMA flow diagram and articles frequency in different years, respectively.

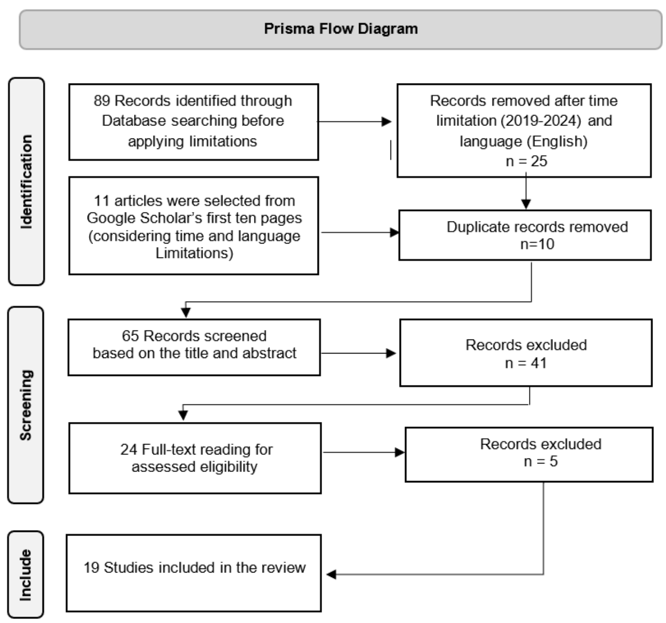

Figure 1. Flow of articles identification and selection based on the PRISMA protocol

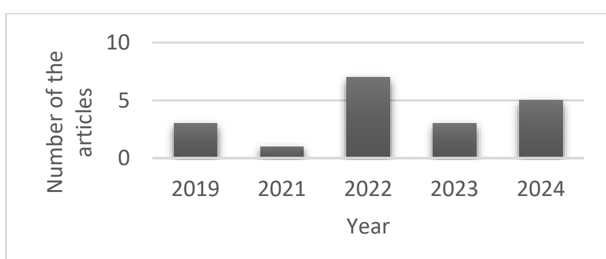

Figure 2. Frequency of articles in different years

3. Findings

In this systematic literature review, articles are categorized based on their approach to utilizing customer feedback within the Kano model, particularly focusing on whether the studies use textual data such as customer reviews and unstructured feedback or rely on structured data or traditional inputs. This classification aims to highlight the different methodologies employed to enhance the Kano model within each category.

3.1 Articles Using Text Mining, Online Reviews, and Customer Reviews

The reason for grouping these articles is that they all rely on textual data from user interactions, such as online reviews, feedback, or other forms of user-generated content, to extract insights. By applying text mining, sentiment analysis, and natural language processing (NLP) techniques, these studies aim to improve product or service offerings based on the voice of the customer. This approach is particularly useful for capturing user preferences dynamically and allows organizations to respond more effectively to evolving needs. Several studies use advanced AI models, such as neural networks, clustering algorithms, or other machine learning tools, to process unstructured text and enhance the classification of product attributes based on the Kano model.

The I-Kano framework, presented by Chen et al. (2019), integrates AI and machine learning (ML) techniques with the traditional Kano Model. The authors aim to establish a systematic method for identifying, evaluating, and classifying product features (PFs) from customer reviews (CRs), providing a more dynamic, data-driven, and user-centered understanding of customer sentiment. The I-Kano framework consists of three main modules: sentiment analysis, feature classification in a three-dimensional space, and anomaly and novelty detection. Sentiment analysis, using NLP methods and Term Frequency-Inverse Document Frequency (TF-IDF) weighting, is performed to derive product features and evaluate customer satisfaction and dissatisfaction. The classification module then categorizes features into Kano's categories based on aggregated sentiment scores, while the added third dimension improves classification, particularly for features near category boundaries, and facilitates comparison of features within the same category.

In another study by Li et al. (2024), a two-stage model was designed to better reflect how users evaluate products after purchase. By utilizing a large dataset of smartphone reviews, the authors used text mining and sentiment analysis to identify product features and understand customers' evaluations of them. These features were then categorized using the Kano model. The key contribution of this study is the combination of two decision-making stages: one that evaluates must-be features using a non-compensatory rule, and another that weighs trade-offs among the remaining attributes to determine overall satisfaction. The proposed structure is a user satisfaction decision model (USDM) and offers a more realistic and flexible way to predict satisfaction than traditional linear models.

Zhao et al (2024) proposed the strength-frequency Kano (SF-Kano) model to study the travelers' needs in the hospitality industry, which classifies customer needs based on online reviews. The authors employed a quantitative methodology, utilizing web scraping techniques to collect a substantial dataset of online reviews collected from a popular hotel reservation platform in China. Using sentiment analysis techniques, the authors extracted both the strength and frequency of different needs mentioned by travelers. The strength of a requirement reflects the urgency for improvement, while frequency highlights how often travelers mention that requirement. The SF-Kano model provides a precise, data-driven approach to classifying requirements, which improves service quality in a cost-effective manner. The authors performed a comparison using the Analytical Kano (A-Kano) model to examine the benefits of the SF-Kano approach. The results showed that the SF-Kano provides a more precise classification.

Lee et al. (2022) investigated customer satisfaction attributes in hospitality settings. The proposed method was Importance-Kano (I-Kano) to assess the importance of service attributes through customer reviews. This framework integrates term frequency, sentiment analysis, and conjoint analysis to classify attributes based on the Kano categories. The authors used Tripadvisor reviews from hotels in South Korea, applying natural language processing (NLP) techniques. The I-Kano analysis helps find which groups of customers care more about specific product features. This is useful for designing products differently, choosing the right target customers, and using different marketing strategies for each group. The study also introduced the I-Kano matrix, a graphical tool that integrates dual importance and Kano categories to provide a comprehensive understanding of the multidimensional effects of various attributes matrix enables businesses to prioritize those attributes that influence customer satisfaction the most.

Al Amoudi et al. (2022) Introduced an automated approach to classify mobile app features into Kano categories using user feedback from app reviews. In this research, which is conducted in Saudi Arabia, the authors addressed the traditional Kano model limitations of reliance on manual surveys. They utilized NLP and clustering (K-means and Agglomerative Hierarchical) to analyze user sentiment scores and group aspects based on satisfaction and dissatisfaction patterns. Their approach involves two algorithms: one comparing sentiment scores to cluster averages, and another adjusting for aspect presence across apps. The results validated against a user survey with 42 participants and showed that the new approach effectively identifies attractive features that can significantly enhance user satisfaction.

Yang et al. (2024) introduced the BERT-TCBAD-Kano model to enhance user requirement analysis for New Energy Vehicles (NEV) by combining sentiment analysis of online reviews with complaint classification. This model includes three components: product attribute extraction using the Latent Dirichlet Allocation (LDA) model combined with expert knowledge to create an attribute dictionary, user preference identification through the pre-trained BERT model for sentiment analysis, and organizing online complaints with the Text Classification Based on Attribute Dictionary (TCBAD) method. This approach balances emotional biases in online reviews and provides a comprehensive analysis of user feedback. The study indicates that prediction accuracy has improved by 30 percent due to the integration of complaint data with sentiment analysis, highlighting the importance of considering both positive and negative feedback.

Jin et al. (2022) presented a hybrid framework that integrates affective customer feedback with product innovation processes by combining Kansei Engineering and the Kano model to mine online reviews. This approach aims to enhance product design by prioritizing customer emotional needs, which is crucial in competitive e-commerce. By utilizing a substantial dataset from Amazon.com, which includes review sentences on smartphones and cameras, the authors systematically extract relevant affective words through contextual analysis and word embedding. The two-step approach involves extracting customer emotions and clustering product features to link them with specific sentiments. The study showed the need for addressing both functional and affective features in product development, suggesting that effective use of customer feedback can improve product offerings and customer loyalty.

Zhang et al. (2024) addressed the challenges beginner UX designers face in classifying user needs by developing an automated tool that integrates the Kano model with deep learning. The data collection process involved both qualitative interviews and online review mining, specifically targeting the needs of Generation Z users. Unlike other studies that rely solely on textual reviews, this research used a structured Kano questionnaire to assign accurate satisfaction categories. This dual approach not only enriches the dataset but also ensures that the findings are relevant to a contemporary audience.

Seven deep learning models, including RCNN, TextCNN, TextRNN, and others, were trained to evaluate their effectiveness in classifying user needs. The RCNN model was recognized as the most effective, achieving an accuracy rate of 78.77%. This model was used to develop a graphical interface that allows users to input text and receive Kano-based classifications with probability scores. Furthermore, the paper discusses the usability evaluation of the developed text classification tool in comparison to traditional methods, such as the affinity diagram. The authors implement a within-subjects design with a single factor and two levels to evaluate their method's effectiveness. This experiment validated the method and provided insights into the cognitive workload experienced by participants, measured using the NASA-TLX scale. The results indicate that the automated classification tool offers a more efficient and user-friendly alternative to conventional methods.

In another study, Joung and Kim (2022) proposed an explainable Neural Network (xNN) model to classify product features into Kano categories using online customer reviews. The methodology involves a four-step process. First, product feature terminology is extracted from online reviews through word embedding and clustering. Second, sentiment analysis is performed using the Vader tool. Third, a neural network estimates the influence of these sentiments on review star ratings. To improve transparency, Shapley Additive Explanations (SHAP) was used to interpret how each feature contributed to the predicted ratings. Finally, product features are classified based on the Kano framework. The approach was validated using Fitbit product reviews and showed accuracy and interpretability.

Park and Jeon (2022) analyzed customer satisfaction dimensions (CSDs) by integrating advanced machine learning techniques with the Kano model. They introduced a combination of LDA for topic modeling, BERT for sentiment analysis, and Gradient Boosting Machine (GBM), along with SHAP to interpret the impact of each CSD on customer satisfaction. This methodology enhances both the predictive accuracy and transparency of the analysis, addressing a common challenge in machine learning applications. The study analyzed online reviews from Amazon, focusing on smartphones and smartwatches. The findings reveal that customer satisfaction is influenced by a complex interplay of these dimensions, providing valuable insights for product development.

Liu et al. (2024) proposed a framework to analyze customer requirements (CRs) in the mobile gaming domain using online reviews. The process components are CR extraction, sentiment analysis, and CR classification. To extract CRs, the authors used TF-IDF and Word2Vec to identify relevant features. For sentiment analysis, they developed a dualchannel BW-CNN model combining BERT and Word2Vec embeddings to capture both general and domain-specific semantics. To explain how different CRs influence satisfaction, an XGBoost model was trained, and SHAP was used to interpret the results. These insights were incorporated into the S-Kano model, which classifies CRs by combining sentiment intensity and customer attention. Based on data from four popular mobile games in Japan, the study indicated that the BW-CNN model outperformed baseline approaches in review sentiment prediction. The results enhance CR extraction accuracy and provide a more interpretable framework to understand how customer satisfaction and CRs are related.

He et al. (2023) applied data mining techniques to enhance product family functionalities by prioritizing performance improvements based on feature importance and customer satisfaction. They collect customer reviews from e-commerce platforms like Amazon and eBay for a sweeping robot product. The reviews were processed using the Natural Language Toolkit (NLTK) in Python and employed techniques such as TF-IDF to identify frequently mentioned performance features. A performance-structure relationship model was introduced to evaluate the commonality factor for each feature, while sentiment analysis determined the satisfaction. The Kano Model was then used to adjust these factors, which resulted in the development of an improvement priority index for each performance specification.

Bi et al. (2019) proposed an approach that helps transform large sets of online reviews into meaningful insights. The method shows which features are most important to customers, how customer sentiment is regarding each feature, their impact on satisfaction, and how each feature fits within the Kano model. It includes extracting key product attributes through topic modeling (LDA), determining sentiment using Support Vector Machine (SVM), and then assessing how these sentiments influence overall satisfaction using an Ensemble Neural Network Model (ENNM). Based on the results, the authors introduced an Effect-Based Kano Model (EKM) that identifies how the enhancement of CSDs impacts customer satisfaction. They tested the proposed framework on a large dataset of mobile phone and camera reviews, which showed the importance of online review analysis for informed product development.

In another study, Shi et al. (2023) used online reviews to derive product features in China's growing e-commerce market. They introduced an Ensemble Deep Learning Model (EDLM), which is designed for the complex nature of the Chinese language. They also utilized word embeddings (WEs) for finding word-level patterns and character embeddings (CEs) to capture the rich semantics of Chinese characters. They proposed a model that is a combination of a multi-layer Convolutional Neural Network (CNN) for word-level representation with a multi-head Bidirectional Long Short-Term Memory (BiLSTM) network for character-level representation. This model effectively addressed issues like word segmentation errors and out-of-vocabulary (OOV) words.

The authors validated the EDLM through a series of experiments, showing that it outperforms existing models and provides valuable insights into consumer preferences. They employed conjoint analysis to assign weight to each product feature and then classified them using a weight-based Kano model (WKM) to prioritize features based on their impact on consumer satisfaction. This methodology supports product feature enhancement strategies by helping managers prioritize attributes that influence satisfaction and loyalty the most.

Zhang et al. (2023) proposed the UNISON framework to identify and assess customer needs in smart Product–Service Systems (smart PSS), a key component of digital servitization. The framework follows six structured phases aligned with the stakeholder, problem, and surrounding contexts and adopts a data-driven methodology. Specifically, it uses BiLSTM networks to classify user review sentences into product or service-related categories, addressing the heterogeneity of smart PSS. It then applies the Bi-term Topic Model (BTM) to extract latent requirement topics from online reviews on smart cleaning robots, which were collected from the JD.com platform. The extracted requirements are evaluated through sentiment analysis, the IPA-Kano model, and the opportunity algorithm to classify them into Kano categories and prioritize development opportunities.

Table 1. Summary of articles Using Text Mining, Online Reviews, and Customer Reviews

Article	Technique	Application Focus	Strengths	limitations
Chen et al. (2019)	I-Kano, Google Cloud NLP API (for sentiment analysis and feature identification), TF-IDF	Coffee machines	Data-driven approach, high accuracy, monitor changes in customer sentiment over time, and identify unusual sentiment patterns	Bias in customer reviews data, difficulty in detecting subtle sentiments, and potential biases in sentiment analysis
Li et al. (2024)	Word2vec, Lexicon-based sentiment analysis, Utility-based Kano mapping	smartphones	Innovative Methodology, Two-stage satisfaction decision model, Data-driven Kano classification method, high accuracy	Focus on reviews from a single platform, consumer characteristics, and temporal and dynamic behavior analysis are not considered
Zhao et al. (2024)	LDA, Word2vec, HowNet (a Lexicon-based sentiment analysis), SF-Kano classification	Hospitality industry	Data-driven approach, Objective Kano classification based on review sentiment	Potential presence of fake reviews, data collection from a single source, and not considering the changing nature of traveler requirements
Lee et al. (2022)	Term Frequency, Lexicon-based sentiment Analysis, Conjoint Analysis	Hospitality industry	Integrated analysis of frequency, sentiment, and significance, clear visual mapping via I-Kano matrix	Using binary sentiment polarity, and not constructing a product attribute lexicon
Al Amoudi (2022)	NLP, SentiStrength (a Lexicon-based sentiment analysis), K-means, Agglomerative Hierarchical Clustering, TF-IDF	Food delivery Apps	Automated Kano classifications using App reviews, data-rich analysis of user feedback, and sentiment-based clustering for objective app aspect classification	Aspects labeled without considering implementation status or user perception, potential inconsistency due to the time gap between reviews and the survey, tool performance affects clustering, subjectivity in survey aspect definitions
Yang et al. (2024)	LDA, BERT-based sentiment analysis, TCBAD, Kano classification	New Energy Vehicles (NEVs)	Incorporates online complaints alongside user reviews, mitigates emotional bias in review data, and improves prediction accuracy	Potential lack of generalizability due to focusing on the Chinese NEV market
Jin et al. (2022)	Word2Vec, Clustering, Kansei Integrated Kano Model, hybrid sentiment analysis	Smartphones & cameras	Creating a hybrid framework that bridges emotional design and customer satisfaction	Kansei word classification relies on polarity scores, not emotional depth. Sub-task methods like extraction, clustering lack technical progress
Zhang et al. (2024)	TextRCNN, Random Word Embedding, Kano classification	LEGO toys	Rigor Methodology, application of deep learning techniques for text classification, which was validated through user testing	Manual labeling of online comments, limited tool functionality, narrow demographic focus (Gen Z)
Joung and Kim (2022)	Word2Vec, Affinity Propagation (AP) algorithm, Vader (lexicon-based sentiment analysis), xNN, SHAP	Fitbit trackers	High predictive accuracy and interpretability through SHAP	Potential information loss due to filtering out the reviews, sensitivity to review rating mismatch, and hyperparameter settings, Inability to detect indifferent features
Park & Jeon (2022)	LDA, BERT-based sentiment analysis, GBM, SHAP	Smartphones & smartwatches	High predictive accuracy, interpretability through SHAP	Binary sentiment analysis lacks intensity consideration
Liu et al. (2024)	TF-IDF, Word2Vec, BW-CNN (BERT + Word2Vec + CNN), XGBoost, SHAP, S-Kano	Mobile games	Contribution to game development, Addressing the limitations of traditional CR extraction, practical prioritization through S-Kano	Focus on a single game genre limited scope of CRs from a single platform
He et al. (2023)	TF-IDF, Lexicon-Based sentiment analysis, AHP, NLTK, Performance-structure model, and Kano	Sweeping robots	Data-Driven Decision Making, Comprehensive Performance Factors	External constraints not considered; weights for importance, commonality, and satisfaction subjectively set via AHP.
Bi et al. (2019)	LDA, SVM, sentiment analysis, Ensemble ENNM, and the EKM	Mobile phones & cameras	No prior distribution assumption required by ENNM, introduction of an enhanced Kano model (EKM)	Lack of customer segmentation, estimation error due to data variability, need for a large volume of online reviews for valid results
Shi et al. (2023)	Multi-layer CNN, Multi-head BiLSTM, Word & Character Embeddings, Lexicon-based Sentiment Analysis, Conjoint Analysis, Weight-based Kano	Smartphone industry	Customized deep learning model (EDLM) design for the Chinese language, effective extraction of both explicit and implicit product features	Potential accuracy issue due to equal word weighting, high manual workload for data labeling

Zhang et al. (2023)	Bi-LSTM, BTM, SnowNLP sentiment analysis, Importance Performance Analysis (IPA), IPA-Kano model	Smart cleaning robots	Automated user requirement analysis, structured multi-phase framework (UNISON)	Need for Dynamic Updates, Single source of data

3.2 Articles Using Structured Data (Not Text Mining or Online Review)

This group of studies does not use customer textual data, such as online reviews or mined unstructured texts, as their basis for analysis. Their approaches rely on traditional or analytical methods, including structured surveys, simulation-based inputs, and real-time customer interaction data. These studies also integrate AI, optimization, or hybrid models, such as genetic algorithms, support vector (SVR), deep reinforcement learning, and machine learning feature selection, while avoiding the use of online review mining or natural language processing techniques.

Dou et al. (2019) integrated the Kano model with an Interactive Genetic Algorithm (IGA) to make product customization easier and more responsive to customer preferences. The study used the Kano model survey results to classify and rank attributes, and the IGA was used to optimize product configurations. Unlike traditional algorithms, the IGA included customer interaction during the optimization process to ensure that the evolving solutions matched user expectations. The study used an interactive tablet prototype to evaluate how well the Kano-IGA system supported real-time product customization, which resulted in faster product selection while reducing the time and effort required for customers to find their most satisfying product design.

Al Rabaiei et al. (2021) combined the Kano model with data mining to improve the understanding and prediction of customer satisfaction. This study was done in the graduate education sector, and students were asked to participate in a survey asking about various features related to their university. After classifying the service features into Kano categories, they used feature selection techniques to minimize the number of predictive variables. Techniques such as ANOVA, Chi-Square, and Lasso were employed to narrow down the most important predictors. The findings showed that just four features were sufficient to build a model that achieves high predictive accuracy. Among a set of ML models tested, the most accurate predictive outcomes were achieved using XGBoost Regression and Decision Tree, which provided the highest correlation between features and customer satisfaction.

Yang et al. (2022) proposed a sustainable design approach for vehicle-mounted unmanned aerial vehicles (UAVs) by integrating SVR, Analytic Hierarchy Process (AHP), and the Kano model. The SVR was employed to model the relationship between design elements and user preferences. To enhance accuracy, the SVR model was optimized by using grid search and validated through cross-validation. The proposed model is appropriate for handling the fuzzy nature of perceptual data. The results provide a comprehensive framework for understanding both quantitative and qualitative aspects of UAV design preferences. It also helps create more sustainable products by translating user opinions into clear design ideas, supporting both creativity and sustainability goals.

Forootani et al. (2022) introduced a method for optimizing home energy management (HEM) that minimizes electricity expenses while maintaining customer comfort and satisfaction. They applied a Deep Reinforcement Learning (DRL) method known as Deep Q-Network (DQN), which combines Q-Learning with a Deep Neural Network (DNN). This model helps control different household appliances and effectively learns optimal scheduling patterns based on fluctuating electricity prices and desired comfort levels, which brings more efficient and practical energy management solutions. The results of the integrated Kano model in the case study showed that the DQN-based HEM system significantly reduced both electricity costs and dissatisfaction in comparison to the Q-Learning-based model.

Table 2. Summary of articles that used structured data

Article	Technique	Application Focus	Strengths	limitations
Dou et al. (2019)	Kano model, IGA	General product customization	Improves real-time customization through user interaction, minimizes users' effort and steps to reach satisfaction, and combines the Kano model with IGA for better customization efficiency	Dependence on alignment between Kano interviewees and actual customization users, potential drop in effectiveness if user groups differ, extended customization time due to the additional Kano analysis phase
Al Rabaiei et al. (2021)	Kano model, ML (such as XGBoost, and Decision Tree)	Graduate education	Mitigates investment in irrelevant features and improves decision-making by identifying a few key predictors, making the model efficient and practical, and identifying critical features for predicting customer satisfaction	Potential lack of generalizability beyond the UAE University context limits the applicability of the results to other institutions or countries, and the limited dataset size
Yang et al. (2022)	Kano model, SVR	UAVs	Contributions to sustainable product development, predictive Framework for Design Decisions, reducing design feature imitation, and promoting original creative elements	Small sample size, Subjectivity, and cognitive deviation in perceptual data
Forootani et al. (2022)	DQN, Mathematical Kano model	Home energy management	The proposed HEM system effectively decreases power expenses and enhances customer satisfaction.	Focuses only on dissatisfaction, limited to a single smart home, not extended to a grid-level or multiple home setup

4. Discussion

The Kano model categorizes product features based on their impact on customer satisfaction (Jin et al., 2022). When using textual data to capture customer requirements and classify them within the Kano framework, it is essential to understand customers' emotions in their responses toward those features (AlAmoudi et al., 2022). To achieve this, many studies used sentiment analysis techniques to extract and interpret these feelings from online reviews. Among the 19 reviewed papers, 15 utilized textual data sources such as online reviews or user feedback. Within these, various sentiment analysis approaches were employed, including lexicon-based, machine learning-based, hybrid methods, and some where the method was not specified. The remaining 4 studies relied on structured data and did not involve sentiment analysis. Figure 3 presents the distribution of sentiment analysis among the reviewed studies. This figure highlights methodological trends, the most frequent sentiment analysis approaches, and areas where future research can expand.

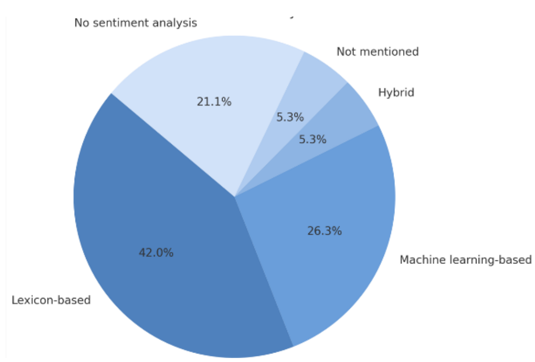

Figure 3. Distribution of Sentiment Analysis Techniques in the Reviewed Studies

While the reviewed studies proposed methods that effectively classify key Kano attributes, some notable challenges remain. For example, Joung and Kim (2022) acknowledged the difficulty in identifying indifferent features. This is a limitation that can reduce the models' usefulness for resource allocation, where recognizing such features is essential to reduce waste and avoid unnecessary investment in developing or enhancing features that neither elevate nor reduce customer satisfaction. Moreover, language structure and linguistic characteristics also play a significant role in the effectiveness of feature extraction and sentiment interpretation, as the unique characteristics of each language may require tailored methodologies for identifying product features and customer satisfaction dimensions from textual reviews. For example, Shi et al. (2023) demonstrated that character-level processing is particularly valuable in the

Chinese language due to the semantic complexity of characters and the absence of word boundaries. Conversely, word-level approaches are generally more effective for English texts. These linguistic differences may challenge the generalizability of the proposed models as their applicability to other languages has not been explored.

Several studies, such as Dou et al. (2019) and Al Rabaiei et al. (2021), rely entirely on structured survey data and numerical optimization methods. While these approaches are effective for quantifying satisfaction drivers, they may overlook more nuanced insights that qualitative data, such as open-ended feedback or customer reviews, could contribute. Other studies, such as Zhao et al. (2024), employed textual reviews to extract and classify features according to the Kano categories, but Forootani et al. (2022) modeled dissatisfaction mathematically without using direct user input. Although this made it easier to connect the Kano model with the AI system and run it automatically, it may limit the model's accuracy in reflecting the actual customer preferences due to the lack of real user feedback. Furthermore, some studies employed hybrid approaches, for example, AlAmoudi et al. (2022) and Shi et al. (2023) involved both online customer feedback and a Kano survey to validate and compare the results of the traditional Kano model with the AI-enhanced application of it. Similarly, Zhang et al. (2024) used a mixed-method strategy and employed interviews with participants, along with mined online reviews, to comprehensively identify user needs.

A common limitation among the structured-data studies is the use of small sample sizes, which can limit generalizability and model robustness. Textual data, on the other hand, offers a scalable alternative by leveraging large volumes of user-generated content. This makes it a promising source for future research, particularly for improving the reliability and representativeness of Kano classifications. Additionally, the reviewed studies differ in how they operationalize the Kano categories when integrating AI, suggesting a need for methodological standardization to ensure comparability and reproducibility across future applications.

5. Conclusion, Limitations, and Future Work

As advanced technologies such as AI emerge, traditional models and methodologies are evolving to adapt to this new era, and the Kano model is no exception. The traditional Kano model approach is valuable, but it cannot analyze and categorize customer satisfaction features in a dynamic, real-time environment. This systematic literature review demonstrates the significant potential of integrating Artificial Intelligence (AI) with the Kano model to enhance quality management and customer satisfaction strategies across industries. AI-powered methodologies, such as text mining, sentiment analysis, and machine learning, allow for the automation of feature classification and more precise identification of customer preferences. The reviewed studies showed that AI-enhanced Kano models outperform traditional approaches by offering real-time insights and predictive capabilities. However, some challenges persist during the implementation of AI in the Kano model, including data quality, survey biases, and complexities in AI technologies, particularly for smaller organizations.

This research also has some limitations. For example, only three academic databases were searched, and only English-language peer-reviewed articles were included. While this helps ensure source quality, it may have excluded relevant non-English or gray literature. So, future studies could address these limitations by expanding the database sources and including studies published in other languages. As many studies propose improved versions of the Kano model tailored to specific industries, future research could consider benchmarking to conduct comparative evaluations of these models to assess their relative accuracy and effectiveness across different contexts or on standardized datasets. Moreover, among the reviewed studies, the majority focused on product sector applications of AI-enhanced Kano models, with only a few addressing service sectors such as hospitality and food delivery. Important areas like healthcare remain underexplored. Future research should consider applying these models in such sectors to improve real-time satisfaction, enhance generalizability, and strengthen their practical relevance.

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Biographies

Mehrnoosh Saeyan is currently pursuing a Ph.D. in Industrial Engineering at the Department of Industrial Engineering and Management Systems at the University of Central Florida. She holds a Master's degree in System Management and Productivity and is a Certified Lean Six Sigma Green Belt. Her research focuses on Quality Management and Continuous Improvement, Customer Satisfaction, and Quality 4.0.

Dr. Ahmad K. Elshennawy is a Professor in the Department of Industrial Engineering and Management Systems at the University of Central Florida. He earned his Ph.D. and M.Eng. in Industrial Engineering from Pennsylvania State University and holds bachelor's and master's degrees in Production Engineering from Alexandria University, Egypt. Dr. Elshennawy has over 30 years of academic and professional experience in quality management, Lean Six Sigma, reliability, and process improvement. He has previously served in key leadership roles at UCF, including Associate Chair, Graduate Program Director, and ABET Coordinator, and has played a major role in advancing academic programs and accreditation efforts. He is a Certified Six Sigma Master Black Belt, a Certified Quality Engineer (CQE), and a Certified Reliability Engineer (CRE). Throughout his career, he had performed multiple Six Sigma projects for organizations across industry and government sectors, including Universal Studios, the U.S. Department of Veterans Affairs, and international entities. Dr. Elshennawy is a Fellow of the American Society for Quality and has authored numerous journal articles, book chapters, and technical publications. He has received multiple awards for excellence in teaching, research, and professional service, including the UCF Excellence in Professional Service Award and several Outstanding Teacher of the Year recognitions.

Dr. Elizabeth Cudney is a Professor and Program Coordinator of Data Analytics at Maryville University's John E. Simon School of Business. She holds an MBA and a Master of Engineering in Mechanical Engineering from the University of Hartford and a Doctorate in Engineering Management from the University of Missouri–Rolla (now Missouri University of Science and Technology). She began her industry career in 1996 with Dana Corporation and in 1998 at Danaher-Jacobs Vehicle Systems as a Six Sigma Black Belt and Senior Manufacturing Engineer. She later transitioned to academia, holding various positions, including Associate Professor and Associate Chair of Graduate Studies at Missouri S&T. Dr. Cudney is an internationally recognized expert in Lean Six Sigma and data analytics, with over 25 years of experience. She has authored and co-authored over 10 books, 14 anthology book chapters, more than 100 refereed journal articles, and over 100 peer-reviewed conference papers. Her recognition includes the 2022 Crosby Medal from ASQ, the 2021 Bernard R. Sarchet Award from ASEE, and the 2021 Walter E. Masing Book Prize from the International Academy for Quality. She is a Certified Lean Six Sigma Master Black Belt and holds eight ASQ certifications, including Certified Quality Engineer, Manager of Quality/Organizational Excellence, and Certified Six Sigma Black Belt. Her areas of expertise include Lean Six Sigma, data analytics, and data visualization.