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AI- Enhanced Kano Model for Data-driven Customer Analytics

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Abstract. *Initially created four decades ago, the Kano model has been extensively used to synchronize product attributes with consumer requirements. Being subjective in nature but offering a subconscious Voice of the Customer (VoC) for managerial decision making, it has been successfully implemented in broad areas of research and practical case studies. From product or service improvements to new design ideas, it proved useful and at the same time attracted criticism. Scholars have proposed over the years a great number of transformations and refinements to the Kano framework, integrating different quality tools with Kano or improving the evaluation stage of the model. Nevertheless, the confusion in use, the great specialized knowledge needed, or the number of statistical tests has discouraged practitioners to adhere to these new approaches. Artificial Intelligence (AI) has recently proven to be helpful in many domains if used properly. The present paper suggests a new methodology to enhance the Kano model results with the use of AI algorithms in a simple and user-friendly approach. In this manner, the AI-Kano method could open doors for a broader and more accurate usage in a variety of domains.*

Keywords: Kano model, Artificial Intelligence, adaptive feedback, customer requirements, customer predictive models, Machine Learning.

Introduction

The Kano model is a recognized paradigm in quality management and customer satisfaction assessment. It offers a systematic method to classify product and service characteristics according to their influence on consumer perceptions (Xu et al., 2009) by categorizing client expectations into five classifications: fundamental (essential or must-be), performance (anticipated or one-dimensional), attractive (surprisingly pleasurable), indifferent (neutral), and reverse (unwanted) qualities. The Kano categorization method has developed significantly since its inception, adjusting to technology improvements, and adding customer preferences indexes (Berger et al., 1993) or new methodologies.

Attributes formerly deemed appealing, such as high-speed internet connectivity, have evolved into fundamental needs, exemplifying the ongoing transformation of customer expectations known as quality attribute lifecycle, especially in our digital world. These changes

DOI: 10.2478/picbe-2025-0084

each product or service feature is going through make the accurate and dynamic assessment of the VoC even more necessary.

The Kano model has become more significant in the digital age, especially regarding service customization and adaptable user experience. Research by Feng and Luo (2024) indicates that the Kano model improves the categorization of user requirements in digital educational platforms, facilitating more effective resource customization.

Despite its critics during the years, the model continues to attract practitioners more than ever. Literature scholars have indeed acknowledged the need for a refinement since the Kano categories are often agglomerated and do not provide enough information for relevant decision-making regarding different product or service features (Potra et al., 2024). But the proposed transformations of the model are very specialized and complicated for practitioners to apply in real situations.

The best refinement of the Kano model should provide a simple method through which managers to clearly understand the importance of each feature and its strategic advantage in their analyzed offer.

The evolution of the Kano model is increasingly associated with artificial intelligence, big data, and predictive analytics, which enhance its adaptability to real-time user preferences. McKay et al. (2024) argue that the integration of machine learning and quantitative methods into Kano enhances predictive decision-making and facilitates dynamic service adaptation. Utilizing the "voice of the customer" (VOC) methodology, digital libraries may enhance service offerings, improve content relevancy, and deliver a more intuitive search experience.

Besides the traditional methods, new approaches should also be taken into consideration. Hemalatha et al. (2024) highlight that AI-driven segmentation can rearrange huge amounts of data from different sources (social media, online records of all sorts) and make connections through spotted patterns and trends. Its current functionalities and real-time adaptation have the power to predict future behavior and thus, enable businesses to enhance product offerings with greater speed and precision (Green and Clarke, 2021).

Therefore, the present paper proposes an interesting research question, namely: Can AI improve Kano subjectivity and category ambiguity, offering a more accurate VOC?

In the next section, this study aims to present through a literature analysis, the evolution of the Kano model and its influence on contemporary quality management. Specifically, it explores the limitations of the traditional model, the proposed refinements and their added-value for practitioners. In the end, the role of AI in customer predictive analysis is explored. Therefore, we can theoretically understand that incorporating AI and adaptive feedback into the Kano model may enhance the precision of the VOC and facilitate the creation of more flexible and adaptable services. An AI-augmented Kano model would have the capacity to automate user categorization using machine learning, providing a reliable differentiation between clustered categories based on objective analysis.

The proposed new methodology for AI-Kano enhanced model will offer a visual process map to follow as a transition from a qualitative Kano assessment to a fully quantitative framework, continued with discussion and conclusions.

Literature review

The Kano model – From usage to refinement explosion

The Kano model remains extensively utilized; however, its applications have substantially expanded to address contemporary product development and consumer satisfaction needs. The classic Kano framework, originally conceived as a qualitative approach, offered significant insights into consumer happiness. Nonetheless, it was constrained in sectors necessitating data-driven decision-making. Over time, several methodological enhancements have been implemented to address these restrictions. Some of them have been synthesized in Table 1.

Table 1. Literature review of Kano transformation proposals

Author(s)	Year	Topic/Section	Main Contributions	Methodology	Key Findings
Kano et al.	1984	Introduction, Historical Development	Introduces the Kano model; categorizes customer needs into basic, performance, and excitement attributes	Theoretical analysis, customer satisfaction studies	Established the foundational concepts of the Kano model, emphasizing non-linear relationships in customer satisfaction
Berger et al.	1993	Introduction, Historical Development, Methodological Comparisons	Explores initial applications and methodological development of the Kano model; differentiates between discrete choice and conjoint analysis	Qualitative analysis, case studies in quality management	Provides an initial framework for applying the Kano model and critiques its limitations in quantitative assessments
Jiao and Chen	2006	Historical Development, Conclusions	Critiques traditional Kano model approaches; emphasizes the lack of quantitative rigor and decision support in product development	Literature review, theoretical critique	Highlights the need for quantitative methods to complement the traditional Kano model for complex product design
Xu et al.	2009	Current Applications, Methodological Comparisons, Future Trends	Introduces the A-Kano model; applies it in automotive design and customer need analysis; suggests future research directions	Analytical modeling, case study in automotive design	Demonstrates how the A-Kano model improves decision-making by incorporating quantitative measures and indices
Lee et al.	2008	Current Applications, Methodological Comparisons, Future Trends	Integrates the Fuzzy method into the Kano model and QFD matrix for better classification of customer demand attributes	Analytical modeling, Fuzzy logic, PLM system case study	Shows that combining Fuzzy logic with the Kano model reduces ambiguity in customer feedback and enhances product design

Author(s)	Year	Topic/Section	Main Contributions	Methodology	Key Findings
McKay et al.	2001	Future Directions	Discusses requirements management and quantitative methods for optimizing product specifications	Analytical framework, product development case studies	Provides a framework for managing customer requirements using quantitative approaches, suggesting future model enhancements
Lai et al.	2004	Methodological Comparisons	Combines Kano and QFD to optimize product design under cost constraints	Case studies, QFD analysis	Shows how Kano can be integrated with QFD for design optimization decisions while adhering to budget constraints
Atlason et al.	2018	Methodological Comparisons, Future Trends	Proposes a rapid Kano-based approach for segmenting customers and identifying functional requirements	Quantitative Kano model application, case study in outdoor sports equipment	Introduces an efficient way to identify optimal customer segments and functional requirements using an extended Kano model
Rotar & Kozar	2017	Current Applications, Introduction	Uses the Kano model to enhance customer satisfaction in home appliances	Survey, factor analysis, Kano model integration	Identifies factors driving customer satisfaction and repeat purchase decisions, applying Kano model in the home appliance sector

Source: Authors' own research.

Violante and Vezzetti (2020)'s research analyzed the benefits and shortcomings of the model via qualitative and quantitative lenses, emphasizing the necessity for a more organized framework to assist researchers and managers in choosing suitable approaches. Expanding upon the original Kano model, these researchers investigated several alternative methodologies, such as fuzzy models and regression analysis, to enhance comprehension of consumer demands and satisfaction. Their findings demonstrated that, although different approaches yielded varied results, no singular methodology was shown as better than the others. The selection of methodology frequently hinges on the categorization needs of single research. The study emphasized that the Kano model is a crucial instrument in the initial phases of customer satisfaction research. Following initial investigations, researchers generally employ Kano questionnaires to evaluate the findings and categorize product features. Violante and Vezzetti (2020) observed that several quantitative methods use coefficients and functions to quantify the Kano model; nonetheless, the outcomes frequently lack consistency, and no conclusive agreement has been established regarding the most effective methodology applicable across all sectors.

Regarding the studies which employ different quality tools with the Kano model, Xu et al. (2009) established the A-Kano model, which incorporates quantitative metrics to enhance need categorization and facilitate Data-Driven decision-making. This development allows organizations

to assess client preferences with enhanced accuracy, especially in sectors with intricate product design limitations.

Atlason et al. (2018) proposed a rapid implementation of the Kano model, aimed at industries requiring swift adaptation to evolving consumer demands. The study presented a customer segmentation method utilizing Kano classification, allowing companies to swiftly identify the most appealing product features for various market segments. Atlason et al. (2018) assert that this approach holds significant value in sectors like outdoor sports equipment, where customer preferences are subject to rapid change, necessitating swift decision-making regarding product features to maintain competitiveness.

Improvements to the original Kano model have responded to a significant critique: its insufficient provision of concrete decision-making assistance in intricate product design contexts. The transition from a qualitative approach to a quantitative methodology would enhance the Kano model, making it a more effective tool for strategic decision-making in product and service development.

The Kano model has been essential in comprehending client wants; nonetheless, the research highlighted the necessity for future studies to improve the model's capacity to quantify these linkages with more precision. The use of the Kano model for user requirement research is progressively enhanced by developing data processing technologies alongside established methodologies. Feng and Luo (2024) performed research utilizing text analysis through Natural Language Processing (NLP) methods to categorize instructor requirements in digital educational systems, therefore obviating the necessity for large surveys. This method facilitated a more accurate and efficient identification of need kinds than conventional questionnaire-based approaches.

Garibay et al. (2010) utilized a comparable methodology in assessing digital libraries, implementing an automated feedback system to gather and evaluate user replies. The integration of the Kano model with machine learning techniques facilitated a more rapid and flexible categorization of user requirements, enhancing the alignment between digital library features and user demands.

Conventional techniques for categorizing user needs in the Kano model have predominantly depended on human surveys and the statistical analysis of replies. The growing volume of user-generated data and the variety of behavioral patterns need the use of more sophisticated tools for data gathering and analysis.

AI- objective customer prediction analysis

In comparison to conventional approaches, AI integration facilitates a 40% acceleration in need categorization and enhances forecast accuracy for growing user preferences by 25%.

AI-driven predictive analysis enhances the user experience by anticipating demands and proactively modifying services. Feng and Luo (2024) have shown that utilizing machine learning models for behavioral data analysis markedly improves the efficiency of user need categorization. By forecasting user preferences, predictive algorithms may examine historical interactions and discern trends that signify shifts in expectations. This enables digital service providers to modify capabilities dynamically, guaranteeing efficient fulfillment of consumer demands. Moreover, predictive analysis facilitates adaptable digital services, allowing for real-time monitoring of user behavior to ensure ongoing improvement of digital experiences. In educational platforms, AI can identify learning habits of teachers and students and suggest individualized resources, hence enhancing engagement and pleasure.

Using predictive models, AI can examine historical user interactions with digital services and discern new trends. In digital education, the behavioral study of educators might reveal the necessity for sorts of materials. This enables educational systems to proactively provide tailored material, enhancing efficiency and responsiveness.

Research by Garibay et al. (2010) indicated that predictive analysis utilizing deep learning approaches to assess user experience in digital libraries improves the recognition of user requirements for such services. By observing user behavior and their interactions with platform functionalities, AI facilitates real-time modifications to service features. Consequently, consumers have a tailored and enhanced experience, augmenting their engagement and happiness.

Predictive models may assess the efficacy of certain product or service attributes prior to deployment, hence minimizing the necessity for extensive testing and manual feedback procedures. AI can evaluate previous user satisfaction data and recommend modifications that are expected to provide a beneficial effect. This considerably reduces the duration needed for following modifications, guaranteeing that enhancements are executed effectively.

Feng and Luo (2024) have shown that unsupervised clustering algorithms are particularly efficient in categorizing user needs without the need for manual labeling. These algorithms can categorize consumers with analogous tastes and identify growing trends in their interactions with digital educational platforms. Supervised Classification Models can use: Random Forest, Support Vector Machines, Artificial Neural Networks – ANN and others. The automated categorization of customer requirements may be performed with supervised models trained on extensive datasets of user input. A Random Forest model trained on user feedback about their experiences with digital platforms can classify a certain feature as a fundamental necessity, performance requirement, or appealing requirement according to Kano model categories.

Alijoio et al. (2025) explores the K-means clustering technique and the Local Interpretable Model-Agnostic Explanations (LIME) for marketing segmentation and targeting, determining deeper customer insights. Their technique has the potential to be used and linked with traditional methods like the Kano model.

Through the application of neural networks, AI can predict alterations in user preferences and proactively recommend enhancements to services, dynamically modifying the classification of needs in accordance with the Kano model. Through the integration of these methodologies, AI facilitates a more rapid and accurate categorization of user needs, hence minimizing the time and resources required for human data gathering and analysis.

Proposed methodology

The present paper envisages to propose a new methodology which integrates the Kano model with AI, for the final scope of a simple assessment of product and service features.

Figure 1 presents the traditional Kano model which starts with some proposed product or service features (known also as quality attributes) based on which a Kano questionnaire is built. Supposing we would want to assess the main functionalities of a new soft drink for children with an innovative flavor, some of the usual features would be the bottle design, the recycled material used for the overall package, the new proposed flavor, the color of the liquid, a sustainable label, and healthy ingredients. The Kano questionnaire will be targeted to both parents and children, depending on their age.

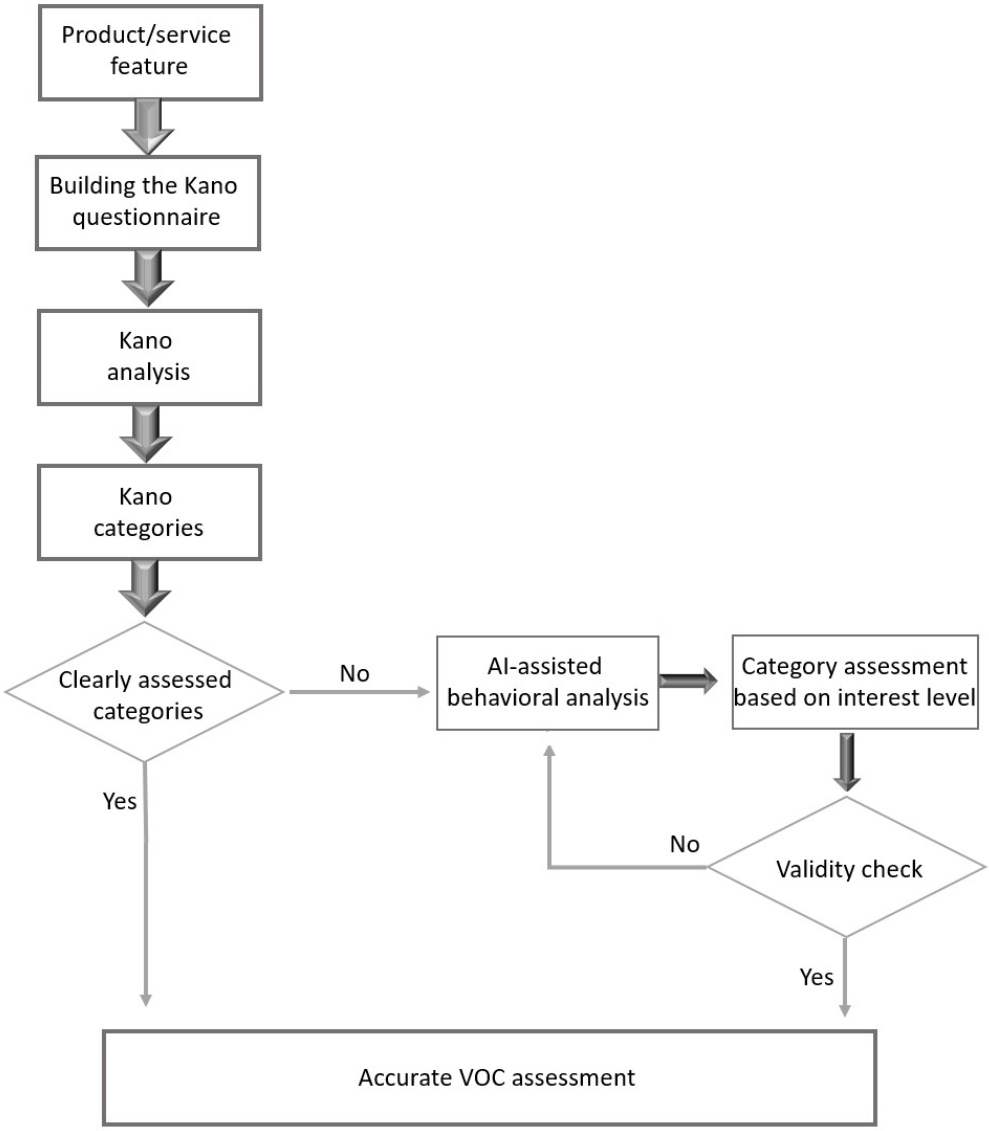

Figure 1. Methodological proposal for AI-Enhanced Kano

Source: Authors' own research.

After responding to a functional and a dysfunctional question for each quality attribute, an expert undertakes the Kano analysis, revealing a particular Kano group for all product features, depending on the customer segment. In this way, if the new flavor is rated as O -one-dimensional, which implies the potential clients desire it, the managerial decision making is simple: to produce it. If the Kano categories are clearly expressed with no doubt about their importance and relevance, we have an accurate Voice of Customer (VoC).

But usually, the decision is not so simple due to quality attribute agglomeration or confusion. Some attributes have close categories (from 100 answers, a feature like the sustainable label could have 42 A- attractive responses and 58 I- indifferent ones, making it difficult to decide if the new label should be implemented or not) or we can observe a clustering of attributes in a specific category (the sustainable label and the recycled material features could be rated as I –

indifferent and we do not have other hierarchy between them for decision making). In these cases, often design engineers would have opted subjectively, having no other decision criteria.

The subjectivity of the decision due to Kano category ambiguity can be overcome with the help of a new methodology which uses AI as an additional tool to traditional Kano questionnaire to refine the results and provide objective decision criteria. The proposed model suggests continuing the assessment of the unclear features using AI-assisted behavioral analysis. In this way, AI can objectively determine the worldwide interest for the unclear attribute and provide a hierarchy for a final decision. For this step, several AI models can be used: Alijoyo's K-means Lime model, Feng and Luo (2024)'s Random Forest, Support Vector Machines, Artificial Neural Networks – ANN and others.

This AI-driven step reduces inconsistencies and enhances accuracy. Subsequently, the data is subjected to a Validity Check to confirm that AI-enhanced classification corresponds with Kano analysis. Discrepancies prompt adjustments, enhancing qualitative attributes prior to finalizing the result for customer options, which offer businesses actionable insights regarding user preferences. The integration of real-time sentiment analysis, predictive modeling, and continuous feedback loops enhances traditional Kano analysis, diminishing dependence on static surveys and facilitating adaptive, data-driven decision-making. The AI-Enhanced Kano Model is especially applicable in digital services, education, and customer experience management, where changing user preferences necessitate a flexible approach to product development and satisfaction evaluation.

Discussions and conclusions

The present study offers a thorough and prospective analysis of the ongoing significance of the Kano model in quality management and product or service design and even development. This guarantees that enterprises not only fulfill but surpass client expectations by delighting them in a continuously changing market.

The use of predictive AI models transforms the Kano model into a dynamic instrument that improves digital service quality, aligns functionality with changing user expectations, and increases satisfaction levels. In this way, the problem with the quality attributes' changing lifecycle is surmounted and a new scalable, data-driven paradigm for enterprises shifting to AI-enhanced decision-making is offered.

The suggested approach facilitates real-time insights, adaptive quality management, and individualized service experiences, therefore influencing the future of customer satisfaction optimization in the digital age.

AI-driven predictive analytics facilitates real-time modification of digital platform features. Classifying customer requirements into Kano model categories through continual input enhances the flexibility and adaptability of products and services. This method results in a considerable enhancement in customer satisfaction, guaranteeing that products and services adapt to evolving demands and expectations.

By integrating this simple to use methodology, we enhance the Kano results, rendering the model more dynamic and effective for analyzing user behavior and preference.

Thus, it tackles the shortcomings of conventional, survey-based Kano analysis by including predictive analytics, natural language processing (NLP), and real-time feedback mechanisms. AI facilitates automated user need categorization and dynamic service adaption using unsupervised clustering and supervised classification models, such as K-means, Support Vector Machines, and Random Forest.

Nevertheless, the proposed model has his limitations. First, the database AI uses is not up to date, usually it does not rely on current data, offering the interest level of last year's information. Secondly, till AI learns from its users, it can provide unclear interest levels. Also, if the practitioner who requests AI this interest level may not know how to manage it correctly. This could happen of the study is performed in Germany for example, but the practitioner does not request trends and segmentation limited to his country. The AI interest level could change the Kano categories since it provides a worldwide perspective which could be different from the German one.

Ethical concerns are also a fact, since the adoption of such technology needs to guarantee the anonymity of individual information retrieved and the transparency of analysis for experts involved.

Future research will focus on developing practical case studies for the suggested model and testing opposed AI techniques and models to offer the best for practical needs for the AI-Kano behavioral analysis theory.

References

Alijoyo, F. A., Aziz, T. S. A., Omer, N., Yusuf, N., Kumar, M. D., Ramesh, A. V. N., ... & El-Ebiary, Y. A. B. (2025). Personalized marketing: Leveraging AI for culturally aware segmentation and targeting. *Alexandria Engineering Journal*, *119*, 8-21.

Atlason, R. S., Stefansson, A. S., Wietz, M., & Giacalone, D. (2018). A rapid Kano-based approach to identify optimal user segments. *Research in engineering design*, *29*, 459-467.

Berger, C. et al. (1993). "Kano's methods for understanding customer-defined quality", *The Centre for Quality Management Journal*, Vol 2, pp. 3-36

Feng, R., & Luo, J. (2024). Analysis of K-12 teachers' demand characteristics for digital educational resource services from the perspective of adaptive feedback: Based on the analysis of KANO model. *Education and Information Technologies*, 1-22.

Garibay, C., Gutiérrez, H., & Figueroa, A. (2010). Evaluation of a digital library by means of quality function deployment (QFD) and the Kano model. *The Journal of Academic Librarianship*, *36*(2), 125-132.

Green, T.E. and Clarke, A. P. (2021). "Optimization of marketing strategies using AI-based customer segmentation," IEEE Transactions on Marketing, vol. 12, no. 3, pp. 112-126.

Hemalatha, R., Amulya, G., and Lalitha, C. H. S. N. S. (2024). "AI-Driven Customer Segmentation for Personalized Marketing," *2024 Second International Conference Computational and Characterization Techniques in Engineering & Sciences (IC3TES)*, Lucknow, India, pp. 1-5, doi: 10.1109/IC3TES62412.2024.10877505.

Jiao, J., & Chen, C. H. (2006). Customer requirement management in product development: a review of research issues. *Concurrent Engineering*, *14*(3), 173-185.

Kano, N., N. Seraku, F. Takahashi and S. Tsuji (1984). "Attractive Quality and Must-be Quality", Hinshitsu. The Journal of the Japanese Society for Quality Control, pp. 39-48.

Lai, X., Xie, M., & Tan, T. C. (2004, October). Optimizing product design using the Kano model and QFD. In *2004 IEEE International Engineering Management Conference (IEEE Cat. No. 04CH37574)* (Vol. 3, pp. 1085-1089). IEEE.

Lee, Y. C., Sheu, L. C., & Tsou, Y. G. (2008). Quality function deployment implementation based on Fuzzy Kano model: An application in PLM system. *Computers & Industrial Engineering*, *55*(1), 48-63.

McKay, A., de Pennington, A., & Baxter, J. (2001). Requirements management: a representation scheme for product specifications. *Computer-Aided Design*, *33*(7), 511-520.

Potra, S., Bogdanovici, L., Baluti, D., Pugna, A. & Sima D. (2024). Refining the HWWP model's customer requirements with AHP's specialist hierarchy for new product design. *11th International Conference on Information Technology and Quantitative Management* (ITQM 2024).

Rotar, L. J., & Kozar, M. (2017). The use of the Kano model to enhance customer satisfaction. *Organizacija*, *50*(4), 339.

Shahin, A., & Zairi, M. (2001). A dynamic approach for classifying and prioritizing requirements of airline travelers with three case studies on international airlines. *Total Quality Management*, 20(9), 1003-1028.

Sun, D., Cheng, G., Yu, P. L. H., Jia, J., Zheng, Z., & Chen, A. (2025). Personalized stem education empowered by artificial intelligence: a comprehensive review and content analysis. *Interactive Learning Environments*, 1–23. https://doi.org/10.1080/10494820.2025.2462156

Xu, Q., Jiao, R. J., Yang, X., Helander, M., Khalid, H. M., & Opperud, A. (2009). An analytical Kano model for customer need analysis. *Design studies*, *30*(1), 87-110.