TOWARDS AN AI-ENHANCED KANSEI ENGINEERING FRAMEWORK

Emil Andersson[1], Noah Löfgren[1] Nuno Valverde[2] Lluis Marco Almagro3, , Simon Schütte[1]

[1]*Linköping University, Linköping, Sweden, simon.schutte@liu.se*

[2]*Logitech Europe SA, Switzerland*

[3]*Universitat Politècnica de Catalunya,, Spain*

ABSTRACT

Kansei Engineering (KE) is a methodology for translating subjective user emotions into tangible product design properties; however, traditional KE relies heavily on manual, labor-intensive, and subjective processes. This work explores the integration of Artificial Intelligence (AI) into the KE workflow to automate and reinforce specific KE-tasks with specialized AI-Tools. To achieve this, the research proposes a novel Multi-Agent System (MAS) framework comprising 21 specialized AI agents designed to operate across the semantic space, product property space, and synthesis phases of KE. Key components, including a Kansei Word Extractor, a Product Property Extractor, and a Synthesis Agent, were prototyped, creating a structured pipeline including language models alongside vision-language models. The framework's performance was evaluated against three historical manual KE case-studies (men's everyday shoes, battery drills, and kettles) and practically applied in a case study on Logitech gaming headphones. Findings indicate that the AI-integrated framework enables rapid ideation, successfully executing a full KE pipeline analysis in under an hour. However, empirical cross-study comparison revealed low cell-by-cell agreement with the manual case-studies. While the AI demonstrated high proficiency in bottom-up, surface-level visual extraction (e.g., shape, color, material), it fundamentally struggled to capture the holistic, non-visual, and ergonomic nuances inherent to true Kansei. The study concludes that while structured pipelines, running smaller AI models, present profound opportunities for scaling data aggregation and mitigating the "black box" phenomenon, they should accompany rather than replace human empathetic judgment.

Keywords: Kansei Engineering, Artificial Inteligence, Large Language Models, Multi-agent AI, Headphones

1 INTRODUCTION

1.1 Background and motivation

Kansei Engineering (KE) is a well-established methodology for translating human emotions and subjective perceptions into tangible product design parameters. Despite its strengths, the traditional KE process is often time-consuming, manually intensive, and reliant on subjective

interpretation. Recent advances in Artificial Intelligence (AI), particularly in large language models (LLMs) and generative systems, offer new opportunities to support and automate key steps in this process.

At the same time, the integration of AI into KE, while emerging in recent years (Liu, 2025), remains fragmented. Individual studies have started to explore AI-supported methods, there is a lack of structured understanding of how these tools map onto the established KE process.

This work is based on a master thesis work carried out at Linköping university by Andersson and Lofgren (2026).

1.2 Artificial intelligence in Product design

Artificial intelligence has become increasingly relevant in product design because it can quickly support the analysis, interpretation, and generation of design-related information. In contrast to traditional design support tools, which often rely on predefined rules or manual interpretation, AI-based methods are able to process large amounts of textual, visual, and numerical data and identify patterns that may be difficult and are time consuming to capture through conventional methods.

Several AI technologies are particularly relevant for product design. Natural Language Processing can be used to analyze textual data, such as user reviews, interviews, product descriptions, and market reports. This makes it possible to extract user needs, emotional expressions, and product-related perceptions from large text sources. Computer vision can support the analysis of visual product characteristics, such as shape, color, proportion, texture, and layout. This enables product properties to be identified and categorized more systematically from image-based material.

Generative AI further expands the role of AI in design by supporting the creation of new product concepts, visual alternatives, and design variations based on given requirements or target impressions. Large Language Models can also assist in organizing design knowledge, generating semantic descriptors, comparing alternatives, and supporting early-stage design reasoning. Together, these technologies make it possible to use AI not only as an analytical tool, but also as a generative and interpretive support throughout the product design process.

For Kansei Engineering, these developments are particularly relevant because the method depends on connecting subjective user impressions with concrete product properties. AI offers new possibilities to support this connection by extracting emotional descriptors from text, identifying visual design attributes from images, and modelling relationships between perception and design features. However, the use of AI in this context needs to be structured carefully so that individual tools are connected to the specific stages and logic of the Kansei Engineering process.

1.3 Research gap and problem formulation

Existing work demonstrates that AI can support specific KE tasks, such as Kansei word extraction or emotional prediction. However, there is limited research that systematically maps

these AI capabilities to the full KE workflow. This raises the following problem: How can AI-supported methods be systematically integrated across the Kansei Engineering process?

The aim of this paper is to analyse and structure the integration of AI into the Kansei Engineering process.

2 KANSEI ENGINEERING THE GENERAL MODEL

The Kansei Engineering process, illustrated in Figure 1, is based on the idea that a product domain can be described from two complementary perspectives: The semantic space, capturing users' emotions and perceptions, and the space of product properties, describing the physical and design attributes of the product Each of these perspectives is represented as a structured "space." In the synthesis phase, the two spaces are linked in order to identify which product properties evoke specific emotional responses. This relationship is then validated and refined through an iterative process, leading to the development of a predictive model connecting product attributes and user perception (S. Schütte et al., 2023).

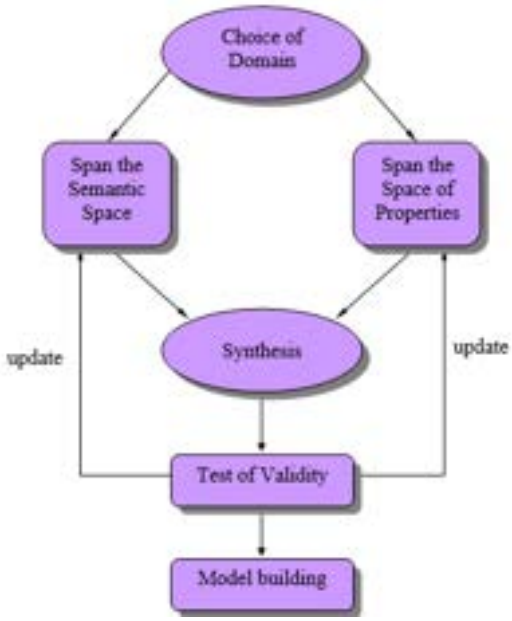


Figure 1 - The general Kansei Engineering model (S. Schütte et al., 2023; Simon Schütte et al., 2004).

2.1 Key components of the Kansei Engineering model and AI-supported extensions

The Kansei Engineering process can be understood as a sequence of structured steps that gradually transform subjective user impressions into concrete product design parameters. In the conventional process, these steps are mainly performed through manual data collection, expert interpretation, user studies, and statistical analysis. In an AI-enhanced process, the same structure can be retained, but several activities can be supported, accelerated, or partly automated through AI-based tools. This makes it possible to preserve the methodological logic of Kansei Engineering while increasing scalability, consistency, and analytical depth (see Table 1).

Table 1 - Kansei Engineering process and AI replacement models (Andersson & Löfgren, 2026).

KE Stage	Analytical Task	AI Toolbox	AI Tool developed
Semantic space	Extract and structure Kansei descriptors	NLP, LLMs	Kansei Word Extractor
Product properties	Identify and categorize design features	Computer vision	Product Property Extractor
Synthesis	Map emotions to design attributes	Machine learning, generative AI	Synthesis Agen

2.2 Choice of Domain

The process starts with the choice of domain. In the conventional Kansei Engineering process, this step involves defining the product domain, target users, market segment, and product scope. Representative product samples are then collected to cover the domain as broadly as possible. This is typically done through market analysis, expert input, competitor analysis, and the manual selection of existing products or concept examples.

AI can support this step by assisting in the identification and structuring of relevant product domains. Large Language Models and web-based AI tools can be used to summarize market trends, identify competing products, and extract relevant product categories from textual sources such as product descriptions, reviews, reports, and online catalogues. Clustering methods can also be used to group products based on similarities in descriptions, specifications, or visual appearance. In this way, AI can help create a broader and more systematic overview of the domain before the detailed Kansei analysis begins.

2.3 Spanning the Semantic Space

The semantic space represents the emotional and perceptual dimension of the product domain. In the conventional process, this step focuses on collecting Kansei words that describe how users perceive and emotionally respond to products. These words are usually gathered from literature, interviews, questionnaires, expert workshops, product reviews, magazines, advertisements, and design references. The collected words are then reduced and structured, often through the Semantic Differential Method, where users evaluate products on bipolar adjective scales such as simple–complex or elegant–rough. Statistical methods such as factor analysis, principal component analysis, or clustering are then used to identify underlying semantic dimensions.

AI can support the construction of the semantic space through Natural Language Processing and Large Language Models. NLP methods can be used to extract emotionally relevant words and expressions from large textual datasets, such as online reviews, user comments, interviews, forums, and product descriptions. Large Language Models can further support this process by generating candidate Kansei words, refining word lists, removing duplicates, grouping similar terms, and suggesting bipolar adjective pairs. Embedding-based methods can represent words as vectors, making it possible to calculate semantic similarity and cluster descriptors automatically. This allows the semantic space to be constructed from larger and more diverse data sources than would normally be feasible in a manual process.

2.4 Spanning the Space of Product Properties

In parallel with the semantic space, Kansei Engineering also requires the construction of the space of product properties. In the conventional process, this step involves identifying the physical and design-related attributes that characterize the selected product domain. These attributes may include shape, color, material, texture, size, proportions, interface elements, component layout, and other observable product characteristics. Manual methods such as expert analysis, brainstorming, affinity diagrams, Pareto analysis, and focus group evaluations are often used to collect, organize, and prioritize relevant product attributes.

AI can support this step by using computer vision and machine learning methods to identify and classify product properties from visual material. Image recognition models can analyze product images and detect relevant design features such as shape, color, texture, proportions, and component configuration. Pre-trained vision models and convolutional neural networks can be used to extract visual features, while clustering algorithms can group products or components according to visual similarity. Classification methods can also help categorize design attributes and identify dominant product characteristics across a dataset. This enables a more scalable and consistent construction of the product property space, especially when many product examples are available.

2.5 Synthesis

The synthesis step connects the semantic space with the space of product properties. In the conventional process, this means identifying relationships between Kansei words and product attributes. The goal is to understand which design features contribute to specific emotional or perceptual responses. This can be done qualitatively through expert judgement, design interpretation, and QFD-like reasoning, or quantitatively through regression analysis, conjoint analysis, neural networks, and other statistical modelling techniques.

AI can strengthen the synthesis step by modelling complex relationships between emotional descriptors and product attributes. Machine learning models can be trained to predict user perceptions based on product features or to identify which features are most strongly associated with specific Kansei words. Regression models, decision trees, random forests, support vector machines, and neural networks can be used depending on the type and amount of data available. In addition, generative AI models can be used to translate semantic targets into new design concepts. For example, image generation or diffusion models can generate product concepts intended to express Kansei words such as elegant, robust, playful, or comfortable. In this way, the synthesis step can move beyond analysis and become a generative design activity.

2.6 Test of Validity

The test of validity examines whether the Kansei model accurately represents the relationship between user perception and product properties. Conventionally, this may involve comparing predicted and observed user responses, conducting additional user evaluations, and revising the semantic space, product property space, or synthesis model.

AI can support this step by testing model performance, identifying inconsistencies, and comparing new user feedback with predicted Kansei responses. However, because emotional perception is context-dependent, human evaluation remains necessary. AI should therefore support, rather than replace, human judgement in validity testing.

2.6.1 Model Building

In the final step, the results of the Kansei Engineering process are combined into a model that describes how product properties influence user perception. Conventionally, this model may take the form of design guidelines or a predictive model linking product attributes to Kansei responses.

In an AI-enhanced process, model building can instead become an integrated design-support workflow that combines language models, computer vision, machine learning, and generative AI. Such a system can support the extraction of Kansei descriptors, identification of product properties, modelling of emotion-design relationships, and generation of design alternatives. However, human interpretation remains essential to evaluate the relevance and meaning of the AI-generated outputs.

3 PROOF OF CONCEPT

To demonstrate the practical applicability of the proposed AI-enhanced Kansei Engineering (KE) framework, a proof-of-concept study was conducted. The study applies the AI toolbox introduced in Chapter 3 to a real product domain, allowing an evaluation of how effectively AI can support different stages of the KE process. The models were tested, trained and validated with previous published KE case studies, in the design of power drills (Grimsaeth et al., 2016), mens' shoes (Van Lottum et al., 2006) and kettles (Mamaghani & Tajoddini, 2010). Upon validating and understanding the usefulness of the developed multi-agent AI pipeline (KE-MAS), a new and more contemporary dataset emerged with gaming headphones from Logitech and its competitors.

The purpose of this proof of concept is to apply the AI-supported methods described in Chapter 3 within a complete Kansei Engineering workflow. The intention is to demonstrate the potential of AI tools to replace or augment traditional KE methods in the generation of the semantic space, the definition of product properties, and the synthesis between these domains. Rather than aiming for full validation of performance, the study focuses on demonstrating feasibility and exploring how AI can support the execution of a full KE pipeline.

3.1 Materials

The image material consisted of 15 commercially available gaming headphones, samples selected to represent visual variation within the product domain. These are shown in Figure 2. The samples were retrieved from online retailers and included headphones displaying different designs and brands. This allowed the Product Property Extractor to identify recurring components and design variants across the domain, such as the headband, ear cushions, ear cups, and microphone boom. The samples were therefore not selected to represent a statistically complete market overview, but to offer a testbed for the AI-supported Kansei Engineering pipeline.



Figure 2 - A dataset of 15 gaming headphones were used for this study (Andersson & Löfgren, 2026).

3.2 Method

The study applied the developed multi-agent AI pipeline (KE-MAS) across the Kansei process (Andersson & Löfgren, 2026). This allowed a full Kansei pipeline execution without direct involvement of human participants.

3.2.1 Step 1: Kansei Word Extraction

In the first step, textual user data were analyzed to identify Kansei words describing users' emotional and perceptual responses to gaming headphones. Different text sources were considered, including product-specific reviews, general headphone reviews, and UX data from Logitech. The purpose was to generate a semantic space that reflected how users describe and experience the product domain.

3.2.2 Step 2: Product Property Extraction

In the second step, product images were analyzed to identify visible design components and product properties. The AI system decomposed the headphones into components such as headband, ear cushions, ear cups, and microphone boom. For each component, design variants related to shape, material, color, articulation, and ornamentation were identified.

3.2.3 Step 3: Application of the Synthesis Agent

In the final step, the extracted Kansei words were connected to the identified product properties. The Synthesis Agent evaluated how different design variants were associated with selected Kansei words and generated design configurations for target impressions such as appealing, elegant, and comfortable. These configurations were then used to create visual product concepts, demonstrating how AI can support the full Kansei workflow from user perception to design output.

4 RESULTS

The results are presented according to the three main steps of the AI-supported Kansei Engineering pipeline: Kansei Word Extraction, Product Property Extraction, and Synthesis.

4.1 Step 1: Results from Kansei Word Extraction

In the first step, three types of textual data were compared: product-specific reviews, general headphone reviews, and UX data from Logitech. The UX dataset produced the most relevant

semantic space for the proof of concept, since it contained more product-specific and design-relevant descriptions of user perception. In contrast, the general review data included a larger amount of functional and post-use evaluations, such as comments related to sound quality, technical performance, or long-term use.

The extracted Kansei words from the UX data included descriptors such as comfortable, appealing, lightweight, elegant, soft, stiff, intuitive, ergonomic, stable, and solid. These words describe both visual and tactile impressions of the headphones and were therefore suitable for the following synthesis step. The result indicates that the quality and focus of the input data strongly influence the semantic space generated by the AI pipeline.

4.2 Step 2: Results from Product Property Extraction

In the second step, the AI system analyzed the headphone image dataset and decomposed the products into four main components: headband, ear cushion, ear cup, and microphone boom. For each component, the system identified visible design properties such as shape, material, color, articulation, and ornamentation.

Across these components, the system identified 22 design variants. Examples include curved or angular shapes, soft or rigid materials, black or vibrant colors, flexible or fixed articulation, and simple or colorful ornamentation. The result shows that the AI system was able to generate a structured product property space based on visual information from the image dataset. This demonstrates how computer vision and multimodal AI can support a task that is traditionally performed manually through expert analysis.

4.3 Step 3: Results from the Synthesis Agent

In the final step, the extracted Kansei words were connected to the identified product properties. The Synthesis Agent evaluated how different design variants contributed to selected Kansei impressions and generated design configurations for target words such as appealing, elegant, and comfortable.

The configuration for appealing emphasized expressive and visually dynamic features, such as vibrant colors, colorful ornamentation, and a more gaming-oriented visual appearance. The configuration for elegant was characterized by restrained design choices, including black colors, simple ornamentation, curved shapes, and a more minimal visual expression. The configuration for comfortable emphasized soft materials, rounded forms, flexible structures, and deep ear cushions.

These results were translated into visual headphone concepts Figure 3. The generated concepts were distinct and coherent in relation to the target Kansei words, suggesting that the AI pipeline can support the movement from user perception to product property analysis and further to early design concept generation. At the same time, the synthesis was strongest for visually inferable impressions, while qualities that depend on long-term use or technical performance remain more difficult to assess through image-based AI analysis alone.



Figure 3 - Rendering of headphones corresponding to certain feelings and emotional descriptors: left: “appealing headphones”, center: “elegant” headphones, and right: “comfortable” headphones (Andersson & Löfgren, 2026).

5 DISCUSSION

The proof-of-concept study shows that AI can support the main stages of the Kansei Engineering process, from extracting Kansei words to identifying product properties and generating design concepts. The results suggest that AI can make the process more efficient and systematic, especially in the early phases of analysis and ideation.

However, the study also shows that the quality of the results depends strongly on the input data. The UX dataset produced more relevant Kansei words than general online reviews, which indicates that AI-supported KE requires carefully selected and context-specific data.

The pipeline performed best for Kansei impressions that can be visually inferred, such as appealing, elegant, and comfortable. Qualities related to long-term use, sound performance, technical reliability, or deeper ergonomic experience were more difficult to assess through image-based AI analysis alone.

Overall, the results indicate that AI should be seen as a support tool rather than a replacement for human expertise. The generated concepts can serve as useful starting points for designers, but they still require interpretation, refinement, and validation by humans.

6 CONCLUSIONS

The main conclusion from this work is that AI can be integrated into the established Kansei Engineering structure without replacing the overall model as Figure 4 shows. The contribution is therefore not a new Kansei Engineering process, but an AI-supported extension of the existing one. Figure 4 illustrates how AI tools can be positioned within the traditional workflow to support selected stages while preserving the basic logic of the method.

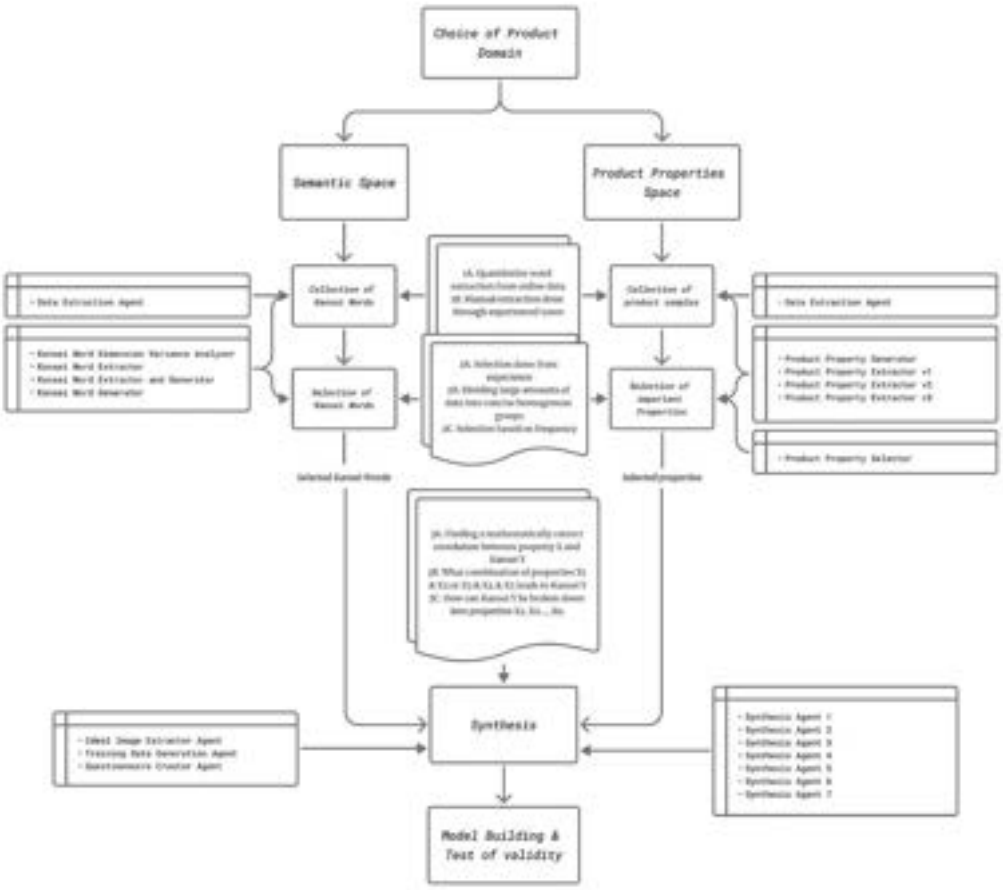


Figure 4 - The general Kansei Engineering model enhanced with AI tools.

AI should however not be treated as one general-purpose tool in Kansei Engineering. Different AI technologies support different tasks. NLP and large language models are suitable for extracting and structuring Kansei words, computer vision can support the identification of product properties, and generative AI can be used to support synthesis and concept visualization. This means that AI integration in KE should be understood as a toolbox, where different tools are matched to specific methodological tasks.

The framework also shows that AI is especially valuable in the early and resource-intensive stages of Kansei Engineering. Collecting user expressions, analyzing large amounts of text, identifying product properties from images, and generating early design directions are all tasks where AI can reduce manual effort and increase speed. The proof of concept with gaming headphones confirms that the proposed structure can be applied in practice, moving from user data to product properties and finally to visual concept generation.

At the same time, the integration of AI introduces important risks. Since AI can automate or simulate many steps of the process, including user-like ratings, there is a risk that human interaction is removed too far from a method that is fundamentally intended to support customer-focused product development. Just because AI can replace a certain activity does not

mean that it should. In Kansei Engineering, human judgement and real user input remain essential for ensuring that the results reflect meaningful emotional responses rather than only AI-generated approximations.

A final conclusion is that AI-generated results can be difficult to question because they often appear coherent and convincing. This creates a risk that incorrect or weakly grounded outputs are mistaken for valid results. Therefore, AI-supported Kansei Engineering should include critical human review, transparency in how results are generated, and validation with users or experts. AI should be used as a structured support system, not as an autonomous replacement for the human-centered foundation of Kansei Engineering.

7 ACKNOWLEDGMENTS

The authors would like to express their appreciation to Logitech Europe SA., for the continuous and extensive support to this research.

8 REFERENCES

Andersson, E., & Löfgren, N. (2026). *Evaluation and Integration of AI in the Kansei Engineering Process*. Linköping University.

Grimsaeth, K., Gangwar, M., Baggerud, B., & Narain, R. (2016). Kansei Engineering Based Emotional Product Design: An Illustration by a Battery Drill Case-Study. *Kansei Engineering International Journal*, *9*(2), 67–79. https://doi.org/10.5057/kei.9.67

Liu, J. (2025). AI in Automated and Remote UX Evaluation: A Systematic Review (2014–2024). *Advances in Human-Computer Interaction*, *2025*(1). https://doi.org/10.1155/ahci/7442179

Mamaghani, N. K., & Tajoddini, M. (2010). Design with emotional approach by implementing kansei engineering-case study: design of kettle. *International Conference on Kansei Engineering and Emotion Research*, 8.

Schütte, S., Mohd-Lokman, A., & Marco-Almagro, L. (2023). *The general Kansei Engineering model*.

Schütte, Simon, Eklund, J., Axelsson, J. R. C., & Nagamachi, M. (2004). Concepts, methods and tools in Kansei engineering. *Theoretical Issues in Ergonomics Science*, *5*(3), 214–231. https://doi.org/10.1080/1463922021000049980

Van Lottum, C., Pearc, K., & Coleman, S. (2006). Features of Kansei engineering characterizing its use in two studies: Men's everyday footwear and historic footwear. *Quality and Reliability Engineering International*, *22*(6), 629–650. https://doi.org/10.1002/qre.803