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RESEARCH ARTICLE

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ABSTRACT

Kansei Engineering (KE) has shown its prominent applicability in service design and development, focusing on translating and interpreting customers' emotional needs (Kansei) into service characteristics. It is critical and promising as the services sector has grown faster than the manufacturing sector in developing economies in the past three decades. It accounted for an average of 55% of GDP in some developing economies. KE's flexibility in collaborating with other methods and covering various service settings shows its unique superiority. However, there is criticism of the collected Kansei's validity and the proposed solution's robustness. It might be potentially caused by the dynamics of customer emotional needs and various service settings. As a result, Kansei is found to be somewhat fuzzy, unclear, and ambiguous. Hence, a more structured KE methodology incorporating the Kansei text mining process for robust service design is proposed. Kansei text mining approach will extract and summarize service attributes and their corresponding affective responses based on the online product descriptions and customer reviews. The Taguchi method will support the robustness of the proposed improvement strategy. An empirical study of a zoo as a tourism attraction service and its practical implication is discussed and validated in the proposed integrative framework.

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Kansei engineering; robust design; mining methodology; service innovation

Relevance statement

This study is relevant to human factors engineering in terms of the role of affect or Kansei incorporating online review mining methodology. Through a focus on attractive qualities of service attributes and robust improvement strategy, this study enables service providers, managers, and practitioners to establish the extent to which they prioritise their continuous improvement strategies, aiming customer delight beyond satisfaction.

1. Introduction

An emotion-based methodology has contributed to product/service development and innovation. One of the notable methods for emotional or affective design is Kansei Engineering (KE). KE has been applied intensively to product design and development since the 1970s

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and has proven its pinnacle of success through the launch of Mazda Miata, taking into account the concept of jinba ittai, a unified feeling of a rider and his beloved horse. It is the first and foremost product design and development methodology considering the user's and customer's emotional needs and satisfaction. Dahlgaard et al. (2008), in KE design, stated that everyone, from children to the elderly, has a hierarchy of values in their lives, and they want to improve their quality of life by using quality products and services.

KE is one of the product development methods used as an interactive interface to design and redesign products and services to make them impressive and emotionally attractive to the users. KE is a psychological method that utilizes unique ergonomic technology for understanding and translating the customer's feelings and impressions into the product and service parameters. As a result, it creates more comfortable and emotionally appealing products or services to meet the customers' expectations. KE catalyzes a systematic framework of new product and service design and development. Moreover, it supports the improvement process for the existing products or services. One of the critical success factors of this method is when it can fully obtain the deepest layer of customer need known as latent need and realize it into the design parameter (Hartono 2020b). Related to this issue, Kano's categorization model is robust in refining and enhancing the KE methodology (Hartono and Tan 2011). Specifically, Kano's attractive (A) and one-dimensional (O) categories are comprehensively found to be the drivers of emotion/Kansei.

KE is a function of the perceived product characteristics' performance. It can be either a linear or non-linear function. In other words, it connects the emotional response (Kansei) to the perception of product performance. Some similar popular tools/techniques are used for product or service design. Related to the most standard method called the House of Quality (HoQ), KE is a kind of development of how to link the whats (functions or needs or voice of customers) into the hows (forms or metrics or engineering characteristics). For example, design for Six Sigma (DFSS) translates customer expectations into design characteristics. This tool generates some design alternatives, chooses the most effective design, tests it in the market, and verifies that it has met the standards (Hasenkamp 2010; Wang, Yeh, and Chu 2016). TRIZ (The Theory of Inventive Problem Solving) is an innovative tool used for product design and development by understanding problems as systems, generating concepts of an ideal solution, and promoting product performance by minimizing potential contradictions (Altshuller 2000).

KE and its application have been extended into services (Hartono 2020a). It is a promising research area. Besides product experience, services have significant roles in day-to-day human activities. Inherently, we are now engaged in services daily, ranging from small groceries, and restaurants to telecommunication, health care, and complex logistic services. Once emotionally satisfied, customers in service encounters will show the same total satisfaction as product experience. More interestingly, a study by Carreira et al. (2013) discussed the KE application in product and service design (known as Product-Service System/PSS). Their study incorporated customer experience requirements (ERs) into PSS design through in-depth interviews involving experts from different backgrounds. ERs are deemed to be a driver of emotional satisfaction.

KE in services is considered a new field of research. It is service innovation that improves service productivity and performance by integrating both psychological and engineering ideas. A combined service system of food automated transport using a robot and the hospitality skill by Nakai-san (skillful service lady) at Hotel Kagaya Japan has shown a significant impact on the service industry. According to Lusch and Nambisan (2015), service innovation may cover a unified framework, i.e. (i) service ecosystems; it facilitates the service actors to exchange service and cocreate values, (ii) service platforms as the venue for service efficiency, effectiveness, and innovation, and (iii) value co-creation; it is a co-creation of value by the service provider and customer.

In the last two decades, several studies have been conducted on applying KE in designing and developing new products and services and reviewing and evaluating product and service designs in offline and online formats. Some research applications of KE and association rules for mining in product design (Pitaktiratham 2012), such as mobile phone affective design (Jiao, Zhang, and Helander 2006; Fuqian, Shouqian, and Jiang 2007; Shi, Sun, and Xu 2012; Fung et al. 2012; and Oztekin et al. 2013), Kanazawa gold leaf, a traditional craft in Ishikawa, Japan (Yan et al. 2008), truck cab (Yang et al. 2008), truck cab interior design (Zhou et al. 2010), interface design of e-commerce web for 3 C products (Wang, Wang, and Chen 2010), clothing design (Xiaoxi, Hui'e, and Zhiya 2017), the packaging design of powder shaped fresheners (Djatna and Kurniati 2015), shoe product (Li et al. 2017), office chair design (Kobayashi and Kinumura 2017), wristwatches (Yamada, Hashimoto, and Nagata 2018), road bike (Chiu and Lin 2018), ceramic (Kittidecha and Yamada 2018), recliners (Kim et al. 2019), computer mouse (Jiao and Qu 2019), mini digital camera (Guo et al. 2014), and digital camera design (Ali et al. 2020).

For practicality and adaptability, Kansei has been represented by emotion-based words, known as Kansei. However, Kansei's words are usually found to be fuzzy, ambiguous, and unclear. More specifically, it happens in the Kansei mathematical model. In addition, it might be due to how to collect Kansei words, i.e. through a face-to-face questionnaire. For instance, the Kansei 'happy' in a luxurious hotel is supposed to be linked ideally and directly to happiness-related service attributes, e.g. the friendliness of staff, the prompt response of staff, or the freshness of lobby odor. The previous study by Hartono (2020b) introduces the importance of Kansei's 'true meaning'. This study proposes a more structured Kansei representative model linked to particular service attributes. Somehow, related to the conventional approach of exploring the Kansei words through a face-to-face questionnaire, it is considered a time-consuming, labor-intensive, and short-lived condition. Due to customer need dynamics and diverse service settings, a more efficient and effective yet robust approach to identify and finalize Kansei is highly required. Thus, the existing Kansei service model needs to be reviewed and modified. The Kansei mining system, which covers historical data of customer Kansei feedback, might be critical to the KE methodology.

2. Recent research on KE in services

The challenge for KE services is the 'true meaning' of Kansei. It is vital to match the perceived service attributes and the representative Kansei (Hartono 2020b). KE in services is much related to integrating service quality tools into general KE methodology. The current approach of KE is more on the general service improvement strategies (Hartono 2020b). Thus, investigating the specific use of KE methodology in service sectors and settings is still prospective and open.

Since the 2010s, KE studies in services have been intensively published, apart from physical products. In general, these studies of KE start with the framework development engaging one or more service quality or statistical tools and end with an empirical study to validate the proposed framework. Through literature review from the publication of KE in services and according to the latest study by Hartono (2020b), the milestones of KE contribution in services are shown as follows:

- KE is assertive in representing the customer's emotional need and satisfaction in the service sector;
- KE is quite adaptive to current issues, trends, and the development of service quality tools;
- KE shows different customer preferences in the different cultural environments;
- KE facilitates the innovative contradiction-free solution approach by incorporating the Theory of Inventive Problem Solving (TRIZ) into the KE methodology for service design. It means that KE supports an innovative contradiction-free solution for services by considering Kansei;
- KE is adaptive to any service quality and statistical tools. It will enhance the utilization and appropriateness of KE in tackling any service excellence issues;
- The sustainability of services is discussed. Specifically, a recent study of KE promotes the mechanism of Kansei called the 'KE-based confirmatory approach for the true meaning of Kansei'.

3. Objectives

This study has two objectives. First, it builds and presents an integrative framework of Kansei Engineering with online review mining for robust service design. Second, a validation of the proposed model through an empirical study. Both theoretical and practical implications will be discussed. This study aims to complement the previous research and its findings on Kansei Engineering in services.

4. Literature review

4.1. Kansei engineering in services

Although not as much as the application of Kansei Engineering in product design and evaluation, research related to the application of KE in service design has been carried out by several scholars, such as in the development of mobile learning (Taharim 2013), home delivery service (HDS) (Chen et al. 2015), cross-border logistics service (CBLS) (Hsiao and Chen 2016), hotel services (Hsiao, Chen, and Lin 2017), hotel service development (Chen et al. 2019), door-to-door delivery service design (Yeh and Chen 2018), airline services (Sukwadi, Uii, and Sanjaya 2018), health care industry (Kittidecha and Kittidacha 2018), and logistics providers (Restuputri, Masudin, and Sari 2020).

4.2. Critics on the conventional method of Kansei engineering

There is a critique of Kansei's traditional methodology. The conventional approach utilizes manual methods, such as surveys accompanied by a questionnaire, to identify product features and emotional preferences and then relate their mutual relationships. Essentially, it is an inefficient process, contributing to time-consuming and one-time activities. Hence, there is an opportunity to develop an unsupervised automated method to explore, identify, generate, and structure affective characteristics information. Kansei text mining has been promoted to extract appropriate information from online reviews and texts, such as product and service affective attributes. The Kansei text mining approach by Wang, Li, Tian, et al. (2018) has been positioned as a methodology for extracting and summarizing product attributes and Kansei responses based on online customer reviews. Efficiently and effectively, customers can review the performance of products and services based on their emotional experiences. It helps customers make purchasing decisions quickly and timely, and also, product managers or manufacturers understand their product positioning against competitors based on customer insights.

4.3. Kansei mining process and methodology

Various studies have proposed Kansei mining for product and service design and development. A study by Bianchi-Berthouze (2001) has proposed Kansei-mining for visual impression identification applied to images and patterns for products. The objective was to reduce the complexity and uncertainty of the mapping between Kansei's response and visual impressions. A conceptual space has been built to provide a formal specification. Cognitive maps have been proposed as a tool to trigger the externalization process for the customer and to support objective reasoning upon subjective trust. In addition, Hayashi, Sato, and Berthouze (2002) showed a hierarchical model for supporting the Kansei mining process. The proposed data bank acted as a support for the mining of multimedia customer feedback. Indeed, it is beneficial to allow data mining at different levels of context and according to multiple interpretations of their content.

Black et al. (2004) proposed natural indexing images based on Kansei levels for retrieval. Similar to the basic methodology of KE, it explores the emotional impressions of a person while viewing an image or object. The emotional impressions may include busy, elegant, romantic, and lavish. The forms of the image impacting the viewer's inner impression are called Kansei. The challenge in Kansei's research is to quantify those factors, with the ultimate goal of indexing images with the 'inner impression' experienced by the viewer. Thus, the focus was on the viewer, not the image, and the similarity measure derived from Kansei's indexing represents similarity in inner experience rather than visual similarity. Their study showed the results of research that indexed images based on a series of Kansei impressions and then looked for a relationship between that indexing and traditional content-based indexing. The goal is to allow indexing of images based on the inner impression they evoke through visual content.

Another interesting study of KE was the application of Kansei mining for mobile phones, proposed by Jiao, Zhang, and Helander (2006) and Shi, Sun, and Xu (2012). A Kansei mining system has been developed to use the customer information of existing designs. The goodness of association rules was evaluated according to customer expectations. The conjoint analysis has been applied to measure a Kansei mapping relationship's expectation and perception of functionalities. The goodness evaluation further refined mapping rules to empower the system with more helpful inference patterns.

Fuqian, Shouqian, and Jiang (2007) have developed a web-based Kansei questionnaire system for generating a Decision Table (DT). It is composed of typical form features (as condition/product/service attributes) and Kansei words (as decision/response/impression attributes) through Semantic Differential (SD) methods. Records are often saved to DT as decision rules indexed by the Kansei word. The proposed method has been successfully implemented in the case of mobile phone design and development. Hotta, Takano, and

Hagiwara (2008) have studied Kansei fuzzy rules mining from photos on the internet. Through the traditional system, Kansei fuzzy rules can be extracted from several questionnaire data and the system also requires a compact yet complex questionnaire survey. The primary purpose of their proposed method is to allow the method to work without questionnaire data being replaced by photo data and tags on the internet. Their proposed method can extract the fuzzy rules of color correspondence with intensive impressions by preparing learning data from the internet and improving the algorithm.

The network platform-based Kansei image survey system (see Figure 1) has been studied by Su and Zhao (2009). Their research utilized the popular application Active Server Pages (ASP) to build a network platform-based Kansei Image Survey System (KISS). First, all kinds of form images of each product are collected through the network search engine to create a database of updated and classified product forms. Second, Kansei image words were structured from related research and interviews to build a Kansei image database related to customer Kansei. Third, according to the SD method, the product form samples and Kansei image words were selected from the product form database and the Kansei Image database, respectively. Fourth, the system automatically generates the network survey questionnaire. The subjects filled out the questionnaire according to the web guidelines. Finally, the researcher obtained the necessary survey data based on the research objectives.

Zhou et al. (2010) have proposed hybrid association mining and refinement for affective mapping in the inspirational design and development of a product or service. Rough sets and K optimal rule finding techniques were applied to identify hidden relationships that underlie future affective mapping. A rule improvement measure was formulated in terms of affective quality. Ordinal logistic regression (OLR) was derived from the backward affective mapping model. Based on the conjoint analysis, the weighted OLR model was developed as a benchmark from the initial OLR model for further refinement. An empirical example of truck cabin interior design was provided to demonstrate the feasibility and potential of a hybrid association mining and refinement (AMR) system to support forward and reverse affective mapping decisions.

Afterward, Dai, Chakraborty, and Shi (2011) proposed a method how to speed up the Kansei retrieval systems by using multi-dimensional indexing technologies using Adaptive R*-tree (AR*- tree for short). This method is deemed more appropriate to Kansei retrieval systems than the traditional multi-dimensional indexing technologies.

Shi, Sun, and Xu (2012) have applied association rule mining and rough sets in Kansei knowledge extraction. They used critical form features and Kansei adjectives defined as condition attributes and decision attributes respectively, which were formalized as two

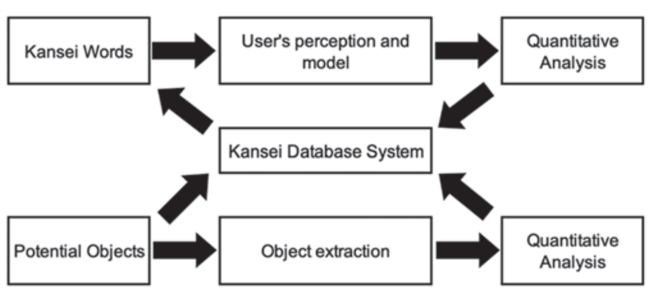

Figure 1. Kansei Database system – objects and Kansei words.

objects in the Decision Table (DT). Evaluation records of individual transaction data were reserved if the frequency was higher than the given threshold. Some form features were removed using an attribute reduction algorithm based on Rough Sets Theory (RST). Afterward, the size of the DT is reduced by using a rule-joining operation. A robust set of association rules describing the relationship between critical form features and their corresponding Kansei adjectives was then generated. Fung et al. (2012) have proposed a multi-purpose genetic algorithm approach for rule mining for affective product design. Kansei robotics as a liaison between humans and electronic gadgets through KE has been studied by Kato (2013). Hsiao and Chen (2016) and Hsiao, Chen, and Liao (2017) have also discussed KE with online content mining for cross-border logistics service design.

A method for collecting and selecting Kansei words to construct a hierarchical Kansei model has been studied by Kobayashi and Kinumura (2017). In their study, they have developed a new method to collect, select, and create a Kansei word hierarchy for an aesthetic design method based on the hierarchical Kansei model. In their proposed method, Kansei word candidates were collected through text mining software, and the most suitable Kansei words for the design target were selected and sorted based on several questionnaire inquiries to customers. Their proposed method can be used for any design method based on the hierarchical Kansei model, especially the one that effectively reduces customer burden because part of the questionnaire results can be reused.

Rule-based back-propagation neural networks for various precision crude sets present Kansei knowledge predictions (Li et al. 2017), mining of affective responses, and product affective intentions from unstructured texts (Wang, Li, Liu, et al. 2018). Yeh and Chen (2018) have discussed how to apply KE and data mining to design door-to-door delivery services. This method quantifies the relationship between service properties, perceived responses, and usage intentions through data mining techniques utilizing decision trees. Yamada, Hashimoto, and Nagata (2018) have proposed a method that automatically builds a Kansei evaluation model for product design using review texts on the web. This method consists of three steps. First, the need to collect and select evaluation words with the word class and Japanese dictionary of evaluation expressions is required. Second, the impression axis is specific to domains with a topic model that uses only estimated evaluation words. Finally, each product for each evaluation axis is scored using the frequency of occurrence of the word evaluation and the term score. In addition, Chiu and Lin (2018) have used text mining and KE to analyze online customer reviews and extract customer preferences to achieve conceptual data-driven design automation and successfully identify future trends in specific consumer products.

Furthermore, Hsiao, Chen, and Liao (2017) and Chen et al. (2019) have implemented big data analytics to support KE for hotel service development. Their research was hoped to provide the hospitality industry with a comprehensive understanding of the opinions of hotel customers. It might offer specific advice on differentiating one's products and services from competitors to increase customer satisfaction and improve hotel performance. Their study also applied KE combined with text mining to develop hotel service guidelines to help managers meet the needs of Kansei customers. Through understanding the online customer comments by text mining, this study has identified Kansei and the most crucial hotel service attributes and then analyzed the relationship among them. These findings provided suggestions for the improvement and development of hotel services. Service development guidelines were set to meet customer needs and can provide advice to hotel managers and practitioners.

In addition, Kittidecha and Yamada (2018) have implemented Kansei Engineering (KE) and Data Mining (DM) into customer-driven product design processes. KE is capable of translating customer emotions into product attributes and engineering characteristics. This method determines the relationship between customer feelings or Kansei words and design attributes. Decision trees and class association rules implemented through the Waikato Environment for Knowledge Analysis (WEKA) software have been used to generate predictive models and find appropriate rules. Chiu and Lin (2018) and Wang et al. (2019) have addressed the online customer product review system to support the KE application. In the Kansei design method, selecting affective variables related to product design elements is essential to capture customer emotions accurately. Therefore, Kim et al. (2019) have developed an affective variable extraction methodology that can effectively and efficiently reflect the user's implicit needs. Their study extracted user affective variables from online reviews and classified them using a self-organizing map (SOM). Text mining and SOM techniques can be used to effectively and efficiently collect and analyze customer affective experiences. Wu and Lin (2018) have explored the e-commerce logistics business model of big unstructured data. In particular, their work developed a hybrid content analytic model to research essential knowledge of e-commerce logistics. In addition, considering the development of natural language processing technology and online shopping, a computerized method for extracting Kansei knowledge from online product reviews was first proposed. A relational extraction method for establishing the relationship between product features and user perception was further proposed. Jiao and Qu (2019) have proposed a Kansei knowledge extraction method based on Natural Language Processing (NLP) technology and online product reviews.

To eliminate differences in individual evaluation criteria in the evaluation of Kansei product attributes and further improve evaluation efficiency, a new automated evaluation and labeling architecture for Kansei product attributes was proposed by Su et al. (2020) based on Convolutional Neural Networks (CNN). The architecture consists of two modules: (1) the target detection module (faster R-CNN is taken as an example) and (2) the exemplary grain classification module (DFL-CNN is taken as an example). Furthermore, Ali et al. (2020) have proposed integrating ontology and natural language processing systems in extracting customer review data within the overall framework. The utility of the proposed approach has been demonstrated through application to a digital camera product review dataset from Amazon, and Hartono (2020b) has discussed the Kansei engineering model methodology using the Kansei text-based mining approach applied to the service.

4.4. Kansei and robust service

According to Hartono (2020c), the conceptual framework of Kansei-based mining, Kano, and SERVQUAL was proposed as a unified model of Kansei taking into account more representative Kansei words and a more robust solution. The objective was to provide a general guideline for service designers and providers in preparing more mature solutions subjected to limited resources (e.g. budget, time, and energy). Ideally, all service attributes are met with particular Kansei. In other words, a Kansei should be, at least, connected to a perceived service attribute. However, faint noise may influence the significant connectivity between Kansei and service attributes.

Moreover, they are pretty sometimes blended into the service offerings. Taguchi or similar methods may be used in determining the optimal service settings by identifying controllable and uncontrollable service factors. The objective is to minimize the noise while maximizing the signal. A recent study for robust service design using Taguchi and Kano model was done by Shanin and Janathyan (2015). Each Kano dimension was assumed to have three different levels. The result showed a modified categorization of the SERVQUAL dimension called robust service design (RSD).

RSD promotes a service or product design which is insensitive to all potential sources of variation. It leads to minimum cost in realizing product or service design. Sources of variation are known as noise factors. Referring to RSD, there are several studies have been conducted. Holcomb (1994) redesigned logistic service quality by proposing a modified signal-to-noise (S/N) ratio. The subsequent study by Macfarlane and Eager (1995) applied the Taguchi method in redesigning the length of stay in healthcare service. In addition, Shahin, Janatyan, and Nasirzaheh (2012) used the S/N ratio to promote the RSD of airport services.

5. Proposed integrative model

This proposed integrative framework refines the previous one by Hartono (2020b). It is completed by adding the step-by-step of how to identify, structure, and finalize the collected Kansei and service attributes using software called KNIME. Some relevant service quality tools were embedded to provide a more efficient and effective result for proposed improvement strategies. In addition, the Taguchi method is added to strengthen the formalized improvement strategies for their robustness. More details it is available in Figure 2.

Inherently, the proposed integrative model of the refined KE with an online review methodology for robust service design consists of 10 sub-steps. It starts with the choice of service domain. More complex human-service interaction and experience will be of interest. There is a close customer and service provider interaction. Currently, environmental awareness will be accommodated, even for both online and offline services (called hybrid services), incorporating sustainability concerns (i.e. people, planet, and profit considerations). Once the service domain is chosen, the collection of raw data is conducted. Online sources, such as social media tweets (e.g. Google Customer Review, Tweets), sales records, and customer feedback and complaints, are used. Relevant pieces of literature (e.g. journal articles, patents, and reputable resources) and expert knowledge/judgment.

Afterward, there is an exploration of spanning the semantic and service space. Through the affinity diagram, the span and refinement of Kansei (semantic space) are structured. It covers the activities: of identifying and finalizing Kansei words and measuring perceived Kansei responses. Concurrently, by utilizing the SERVQUAL and Kano model, there are several activities covered such as identification and refinement of service attributes, measurement of perceived service attributes, and categorization of service attributes according to their impact on satisfaction using the Kano model.

Once the characteristics of semantic space (Kansei) and service space (service attribute) are fully finalized, a synthesis and linear modeling will be conducted. Kansei's response is a consequence of perceived service attributes with the Attractive (A) or One-Dimensional

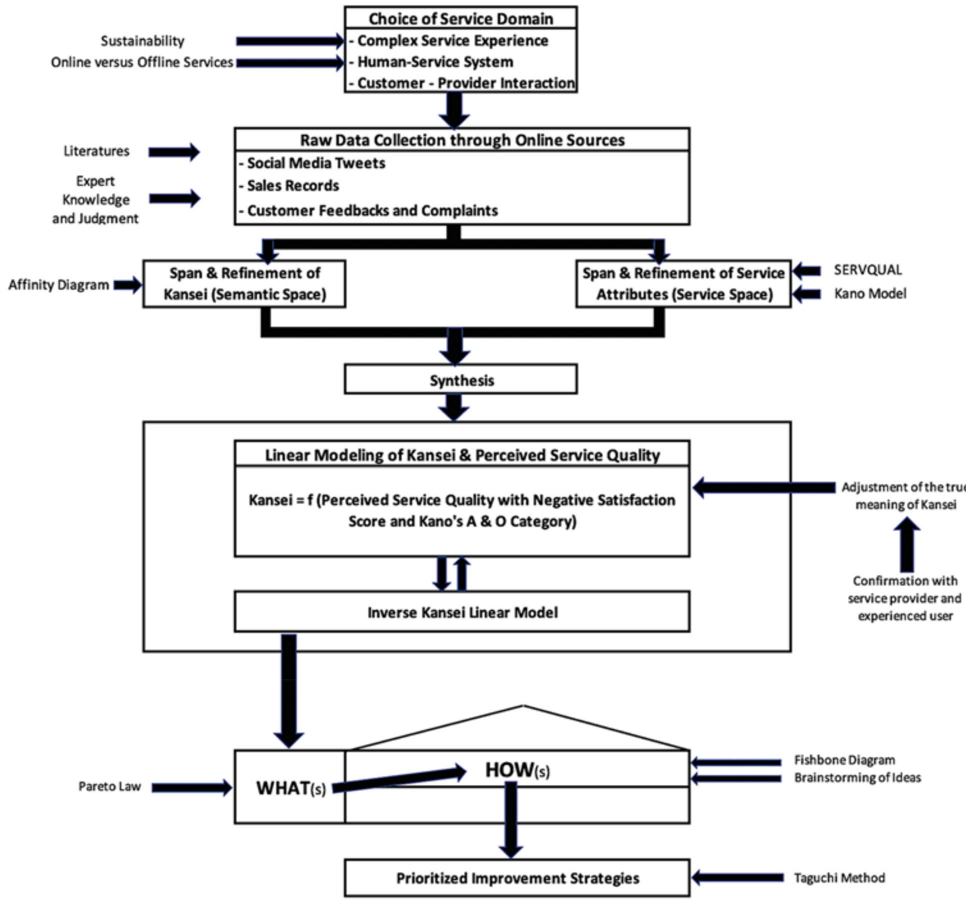

Figure 2. Integrated framework of refined Kansei Engineering with online review methodology for robust service design.

(O) Kano category. The formed Kansei models are then checked and confirmed with 'the true meaning of Kansei'. Next, the Kansei is checked through the accurate perception of service attributes. Kansei linear models are then inversed as to which service attributes are critical to certain Kansei.

The critical service attributes are selected and filtered using the Pareto principle. They are linked to possible metrics or engineering characteristics through brainstorming of ideas and a fishbone diagram. It then continues formulating improvement strategies using the Taguchi method to promote more robust solutions.

6. Case study on zoo services

This zoo is in a mountainous area in Indonesia, one of the largest zoos in the country. It is a tourist place that offers knowledge of animals and has rides on it, called 'XYZ'. The number of similar industries makes the competition in this business very tight. To maintain the brand in the eyes of visitors, the zoo 'XYZ' must improve the quality of service and the satisfaction and feelings of visitors (Kansei). The problem occurs when there is a gap between what is expected and what is perceived by the customer. More specifically, it happens if the perception is lower than the expectation.

Since customer expectation is rapidly growing, fulfilling rational and basic needs is insufficient. The service quality of zoo 'XYZ' can be improved by fulfilling visitors' emotional needs. Therefore, we should not overlook the deepest layer of customer need: affect or emotion. It is hoped that visitors will feel comfortable and enjoy the ambiance.

Text mining was carried out by collecting and processing customer review data from social media. The targeted results were more representative of zoo service attributes and Kansei. This process was done using Knime Analytics software to collect Kansei words. In this process, there are eight nodes to get topics that will be regarded as the output of service attributes which will then be used in structuring the survey instrument (questionnaire). At node 1, it starts from the file reader process, which is the process of reading files obtained from the initial data collection, which results from a review from social media. The reviews in this process utilized 200 reviews obtained from various sources, namely Google, Traveloka, and Trip Advisor. Those 200 customer reviews were collected and considered to have represented a holistic customer experience while at the XYZ zoo. At node 2, it is known as a row filter. The row filter produces the same output as the initial data because there are no empty rows in the inputted data, so the existing data remains the same. At node 3, it is called strings to document. It is to convert the specified string into a document. The resulting output contains data strings from the input table as well as documents created in an additional column, namely pre-processed documents.

Furthermore, node 4, 'number filter', is a process that functions to remove numbers in the pre-processed document. After getting the output of the document that has been omitted, then it is continued to node 5, 'punctuation erasure', which functions to remove punctuation from the previous processes. The next is node 6, known as the stop word filter. It is the process used to remove conjunctions that exist in the system's default process. The output produced by this process is a pre-processed document that has removed the stop words in it. Then it proceeds to the case converter process at node seven, which changes the text in the pre-processed document to lowercase so that there are no capital letters in the pre-processed document anymore. Then the last process at node eight is called the topic extractor. In this case study research, the topic extractor process used ten topics and 15 words to produce 150 words which would then become attributes of the Servqual and Kansei words (Figure 3).

After going through the text mining process, it proceeds with the sentiment analysis based on the results of the case converter to find out the number of words with positive and negative variables. Several processes are needed to get the number of positive and negative variables, which are advanced from the case converter in the text mining process. The entire sentiment analysis process is shown in Figure 4. The output results were 105

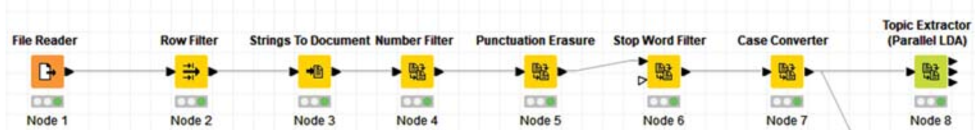

Figure 3. Text mining process for Kansei words and service attributes.

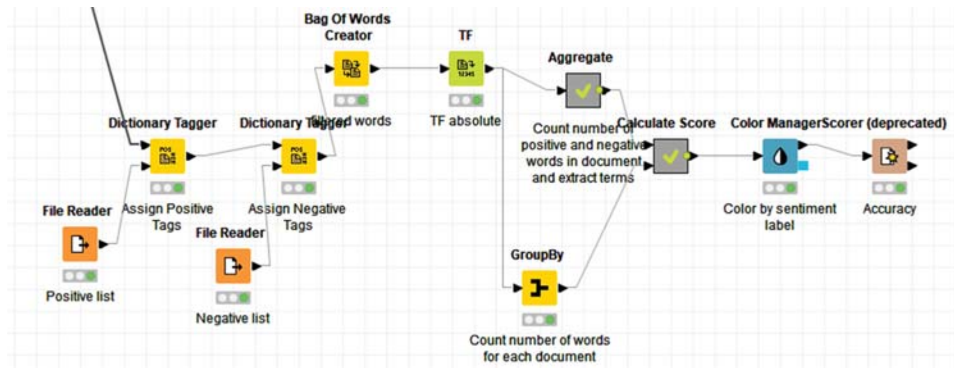

Figure 4. Sentiment analysis process.

negative words, 85 positive words, and 11 words that were not detected in positive or negative variables. It implied that the zoo 'XYZ' needed improvement because it received more negative reviews than positive reviews based on random visitor feedback from several social media platforms.

6.1. SERVQUAL attributes and Kano categorization

Service attributes based on text mining output consider five dimensions of the SERVQUAL model, namely the TERRA (Tangible, Empathy, Reliability, Responsiveness, and Assurance) which has been then validated with previous research. There were 19 final service attributes with the Kano category, perception, expectation gap, and satisfaction score. According to Hartono (2020b), the identification of the main Kano category for service attributes was applied; they consist of attractive (A), one-dimensional (O), must-be (M), indifferent (I), and reverse (R). Kano's model has the potential to augment unspoken or latent human needs, the satisfaction of which can lead to customer satisfaction. Happy customers will remain loyal and refer well to others about the company and its services or products (Hartono and Tan 2011). Both KE and Kano category aim to improve customer (emotional) satisfaction and create successful services. Through Kano model questionnaire (see Hartono and Tan 2011), the Kano categorization of each service attribute has been validated (provided in Table 1). The must-be (M) is considered essential and highly expected by customers. If they are missing, customer satisfaction drastically decreases, but their increased level of presence does not necessarily lead to increased satisfaction. The one-dimensional (O) shows the correlation between service performance and customer satisfaction, and it is usually explicitly asked by customers. The more of these attributes a service possesses, the higher the satisfaction level. The attractive (A) or known as delighter is service attribute which goes beyond customer expectations. Its presence leads to a positive surprise and can significantly enhance customer satisfaction. Once it is missing, it will not create customer dissatisfaction. The other two Kano categories are as follow. Indifferent (I) refers to the service attributes which are neither contributing to customer satisfaction nor causing dissatisfaction. Lastly, reverse (R) has negative impact on customer satisfaction when present, however, its absence will not lead to increased satisfaction.

Table 1. Kano category and satisfaction score for service attributes.

No (Item)	Service attributes	Kano*	Importance	Perception	Expectation	Gap**	Satisfaction***
Dimension 'Assurance'							
1 (A1)	Enjoy – Enjoyable facilities	I	3.911	3.644	4.188	−0.545	−2.130
2 (A2)	Time – Service time as promised	A	3.921	3.802	4.059	−0.257	−1.009
3 (A3)	Cleanliness – Prioritized cleanliness	O	4.040	3.644	4.198	−0.554	−2.240
4 (A4)	Safe – Sense of secure	M	4.218	3.891	4.228	−0.337	−1.420
Dimension 'Empathy'							
5 (E1)	Nice – Staff shows clear direction	I	4.178	3.960	4.287	−0.327	−1.365
6 (E2)	Caring – Staff cares about visitors	I	4.040	3.772	4.208	−0.436	−1.760
7 (E3)	Friendly – Staff behaves friendly	I	4.168	3.980	4.218	−0.238	−0.990
8 (E4)	Happy – Visitor has pleasant experience	A	4.109	4.020	4.208	−0.188	−0.773
Dimension 'Reliability'							
9 (Rel1)	Bus – Ontime bus arrival schedule	I	3.911	3.525	4.139	−0.614	−2.401
10 (Rel2)	Management – Ontime animal attraction show	I	4.040	3.752	4.218	−0.465	−1.880
11 (Rel3)	Parking – Adequate parking space	I	4.208	3.871	4.238	−0.366	−1.542
12 (Rel4)	Price – Appropriate service rates	M	4.050	3.812	4.188	−0.376	−1.524
Dimension 'Responsiveness'							
13 (Res1)	Health – Adequate health protocol	O	4.119	3.881	4.248	−0.366	−1.509
14 (Res2)	Performance – Staff serves promptly	O	3.960	3.762	4.198	−0.436	−1.725
15 (Res3)	Pandemic – Readiness to face the pandemic	O	4.010	3.901	4.119	−0.218	−0.873
Assurance 'Tangibles'							
16 (T1)	Animal – Appealing animal performance	A	4.010	3.871	4.188	−0.317	−1.270
17 (T2)	Direction – Clear road direction	A	4.099	3.901	4.218	−0.317	−1.299
18 (T3)	Food – Comfortable food stalls	M	3.881	3.594	4.119	−0.525	−2.037
19 (T4)	Variety – Various types of animals	A	4.168	3.980	4.267	−0.287	−1.197

*Kano category: A = attractive, O = one-dimensional, M = must-be; **Gap = perception − expectation; ***Satisfaction = importance x gap; grey highlighted shows A&O Kano categorized service attributes.

Once the Kano categorization has been finalized, the scoring process moved to the description of importance, perception, and expectation values, in order to calculate the gap and satisfaction scores. The importance level is measured through a Likert scale with a range of 1 (not at all important) to 5 (absolutely important) regarding the customer experience of 'XYZ' zoo services, whereas the perception and expectation levels are based on the extent to which customer believe 'XYZ' has the service attributes described by the statement, and the extent to which customer think such a zoo would possess the service attributes described by each statement, respectively. Those two measurement also use a 5 level-based Likert. Afterward, the service gap is measured, i.e. the discrepancy between perception and expectation. Finally, the satisfaction score is measured through the magnitude of multiplication between importance and service gap. The higher the (negative) satisfaction score with A or O Kano's category shows the more critical the service attribute is.

Based on Table 1 above, it can be seen that nine attributes were obtained with Kano categories A and O and have a negative satisfaction score value, so it required improvement. Thus, those nine attributes were prioritized. However, the other ten service attributes were proposed to maintain a good standard.

Below is the categorization and mapping of Kano for service attributes (see Figure 5). It shows that 9 out of 19 service attributes (47.37%) are categorized as attractive (A) and one-dimensional (O). There was no Kano's reverse (R) categorized item. Only three items were categorized as must-be (M).

6.2. Kansei words collected as the representative customer emotional responses

The determination of Kansei words has been obtained from text mining using the Knime Analytics software, based on secondary data from the reviews circulated on social media and online platforms such as Traveloka, Google, and Trip Advisor. As a result, there were 10 Kansei words finalized, namely, happy, lovely, enjoyable, friendly, clean, maintained, awesome, safe, satisfied, and love. It was facilitated by affinity diagram, through analysing, organising, and consolidating a large set of Kansei words into a small number and concise set of Kansei representatives. These words represent the impression of people enjoying the zoo attraction and its physical and non-physical surroundings. They were deemed to be independent.

Each Kansei word was assessed in three various measures, i.e. importance, response, and Kansei gap. Regarding the importance, it was done through the rating of importance of emotional needs/Kansei when the customers were experiencing the whole service of zoo 'XYZ' with a scale ranged from 1 (not at all important) to 5 (absolutely important). In term of response score, it was rated according to the real fulfilment of emotional needs (Kansei) of customers in the zoo 'XYZ' with a scale of 1 (the absolute feel of negative Kansei) to 5 (the absolute feel of positive Kansei). Then, Kansei gap was measured according the

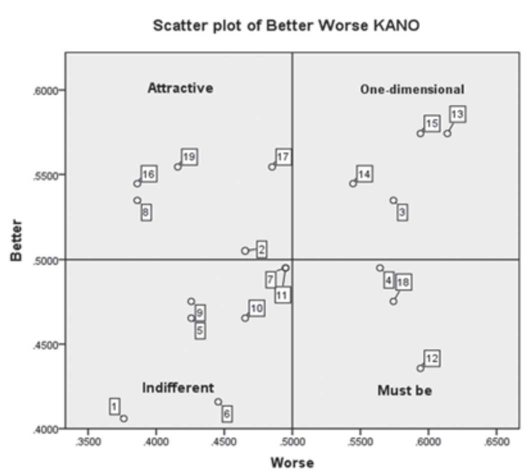

Figure 5. Scatter plot of kano's service attributes.

difference between response and importance. As all Kansei got negative Kansei gap, although they were above score of 4.00. It seemed that the entire experiences in zoo 'XYZ' need to be increased in terms of emotional appeal and feelings (Table 2).

6.3. Linear model and prioritization of service attributes to improve

By incorporating the Kano categorization for all service attributes (especially Kano's A and O) along with satisfaction and perception scores, and Kansei response, Kansei linear models, were provided. Kansei response is a function of the perception of service attributes (see Hartono and Tan 2011). Here, the confirmatory mechanism was applied to promote the realization of the true meaning of Kansei. The 'true meaning of Kansei' is known as a KE-based confirmatory approach. It is to confirm the appropriateness of the Kansei linear model based on the potential discrepancy between the significant linear model and the conventional Kansei relationship. This confirmation is essential to check the appropriateness of Kansei's effect on specific service attributes. Integrating KE, SERVQUAL, and Kano methods using linear regression aims to determine the influential attributes for each Kansei word. It combines those three methods through linear regression analysis of the average Kansei response and the average perceived response of service attributes with a negative score with Kano's A and O categories. The selection of Kano's A and O categories is significantly proven that they are the driver of emotional satisfaction and innovation (Hartono and Tan 2011). Linear model was derived from the multiple linear regression analysis, which is used to predict the value of dependent variable (i.e. Kansei response) based on the value of independent variables (i.e. the perception of zoo 'XYZ' service attributes). This study has assumed that the Kansei and service attribute is positively linearly correlated, though the relationship between Kansei and service attribute might be non-linear form. The significant value of the linear model is represented by p-value with type 1 error of 5%. It is shown that all Kansei words had significant service attribute correlated, except K9 (Satisfied). It might be satisfaction was perceived by the combination of several Kansei words, thus its relationship with service attributes was considered weak (Table 3).

Afterward, the Kansei linear models were then reconstructed. It is called a reversed model. The objective was to identify which zoo service attributes were critical to improving continuously. Based on the previous studies (see Hartono and Tan 2011), the service attributes which are the potential to be followed up for continuous improvement will be captured. These service attributes will be the ones with a high correlation with the

Table 2. Kansei descriptive statistics of zoo experience.

Kansei	Importance	Response	Kansei gap*
K1. Happy	4.535	4.218	−0.317
K2. Nice	4.426	4.178	−0.248
K3. Enjoy	4.515	4.277	−0.238
K4. Friendly	4.505	4.248	−0.257
K5. Clean	4.465	4.059	−0.406
K6. Maintained	4.535	4.149	−0.386
K7. Awesome	4.356	4.158	−0.198
K8. Safe	4.584	4.277	−0.307
K9. Satisfied	4.406	4.139	−0.267
K10. Love	4.396	4.079	−0.317

*Kansei Gap = Response − Importance.

Table 3. Significant linear model.

No	Kansei word	*p*-value	Linear model	Significant service attribute*
K1	Happy	0.005	Happy = 3.338 + 0.226 (T2)	T2 (Direction – Clear road direction)
K2	Nice	0.013	Nice = 3.501 + 0.175 (T1)	T1 (Animal – Appealing animal performance)
K3	Enjoy	0.009	Enjoy = 3.457 + 0.216 (A2)	A2 (Time – Service time as promised)
K4	Friendly	0.001	Friendly = 3.308 + 0.241 (T2)	T2 (Direction – Clear road direction)
K5	Clean	0.004	Clean = 2.962 + 0.281 (Res3)	Res3 (Pandemic – Readiness to face the pandemic)
K6	Maintained	0.001	Maintained = 3.073 + 0.278 (T1)	T1 (Animal – Appealing animal performance)
K7	Awesome	0.001	Awesome = 3.009 + 0.296 (Res1)	Res1 (Health – Adequate health protocol)
K8	Safe	0.002	Safe = 3.214 + 0.274 (Res1)	Res1 (Health – Adequate health protocol)
K9	Satisfied	–	–	–
K10	Loving	0.009	Love = 3.202 + 0.226 (Res1)	Res1 (Health – Adequate health protocol)

*Taken from Table 1 for the description of service attributes.

Kansei characteristics in terms of the number of Kansei, the perception score of Kansei, and the real confirmed Kansei. The modification of the reverse model includes calculating the importance weight of WHAT (called IWW), incorporating the absolute satisfaction score, Kano's weight score, Kansei's mean score, and the number of Kansei affected. In other words, the reconstructed 'importance weight of WHAT (IWW)' is formulated by the multiplication of absolute satisfaction score, Kano weight, an average of Kansei's perception score, and the number of Kansei influenced (see Hartono 2020c). The absolute satisfaction score is derived from the absolute multiplication of service gap and importance score (see Table 1). The higher IWW score, the more critical the service attribute is.

Table 4 shows that the service attribute T2 (Direction – Clear road direction) had the highest IWW score. It means that the zoo service provider should have had provided clear road directions inside the area, including the location of each animal attraction. Indeed, it was a critical service attribute for the customers. At the same time, the lowest score of IWW has been occupied by service attribute E4 (Happy – Visitor has pleasant experience). The Pareto chart was used to prioritize the service attribute's improvement. The Pareto will help designer or manager deciding what problems to address first, by identifying 20% of the causes or problems which lead to 80% of the effects. IWW was considered as the effect due to certain problem. It counted about an accumulative 80% IWW, and its outcome was provided in Table 5 and Figure 6. In other words, once the cumulative percentage reached at least 80%, we will stop the iteration and get the number of service attributes to be prioritised for improvement.

6.4. Prioritized improvement through Taguchi

According to the findings shown in Table 5, there were four service attributes being followed up for improvement. They included T2 (Direction – Clear road direction), T1 (Animal – Appealing animal performance), Res1 (Health – Adequate health protocol),

Table 4. Reversed Kansei linear model and calculation of importance weight of service attributes.

Item	Service attributes	Satisfaction Score	Kano's Category and its Weight		Impacted Kansei and its Mean Score		IWW*
A2	Time – Service time as promised	−1.009	A	4	Enjoy	4.28	17.27
A3	Cleanliness – Prioritized cleanliness	−2.240	O	2	–	–	4.48
E4	Happy – Visitor has pleasant experience	−0.773	A	4	–	–	3.09
Res1	Health – Adequate health protocol	−1.509	O	2	Awesome; Safe; Love	4.17	37.77
Res2	Performance – Staff serves promptly	−1.725	O	2	–	–	3.45
Res3	Pandemic – Readiness to face the pandemic	−0.873	O	2	Clean	4.06	7.09
T1	Animal – Appealing animal performance	−1.270	A	4	Nice; Maintained	4.165	43.32
T2	Direction – Clear road direction	−1.299	A	4	Happy; Friendly	4.235	43.98
T4	Variety – Various types of animals	−1.197	A	4	–	–	4.79

*IWW = |satisfaction score| x Kano's weight x number of Kansei impacted x Kansei mean score.

Table 5. Prioritized improvement for service attributes using Pareto.

Item	Service attributes	IWW	Percentage	Cumulative percentage	Prioritized to be improved?
T2	Direction – Clear road direction	43.98	27	27	Yes
T1	Animal – Appealing animal performance	42.32	26	53	Yes
Res1	Health – Adequate health protocol	37.77	23	76	Yes
A2	Time – Service time as promised	17.27	11	86	Yes
Res3	Pandemic – Readiness to face the pandemic	7.09	4	90	No
T4	Variety – Various types of animals	4.79	3	93	No
A3	Cleanliness – Prioritized cleanliness	4.48	3	96	No
Res2	Performance – Staff serves promptly	3.45	2	98	No
E4	Happy – Visitor has pleasant experience	3.09	2	100	No

and A2 (Time – Service time as promised). The service attribute T2 (Direction – Clear road direction) was selected as the most prioritized item to improve, considering the possible constraints (e.g. time, effort, and budget).

Through literature review and in-depth interviews with the five actual customers of the zoo 'XYZ', there were three compiled improvement components, namely: (1) Provision of picture of the map with fewer wordings, (2) Provision of Augmented Reality (AR)-based location map, and (3) Provision of picture of the map only. The Taguchi methodology with 2-level was proposed according to these three improvement items. The description of the 2-level for each improvement item is provided in Table 6. These 2-level improvement items were deemed to be comparable and fulfilling 'apple-to-apple' option. In other words, there will be a balanced trade-off when we choose either level 1 or level 2 item.

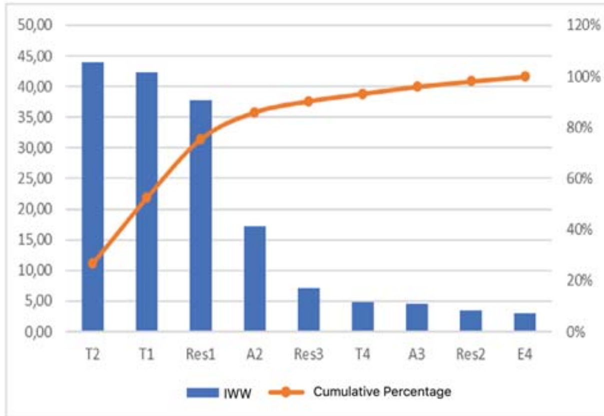

Figure 6. Pareto diagram for prioritized improvement of service attributes.

Table 6. Two-level of improvement items using Taguchi.

Taguchi factor	Improvement element	Level 1	Level 2
A	Provision of picture of the map with fewer wordings	Providing a picture of a map through Quick Response (QR) scan	Providing a physical picture of a map through hardcopy (paper-based)
B	Provision of Augmented Reality (AR)-based location map	Providing an AR-based location map at the entrance gate	Providing AR-based location map at each animal attraction spot
C	Provision of picture of the map only	Setting up a mobile picture of a map	Setting up a fixed picture of a map

Table 7. Response table for means.

Level	A	B	C
1	4.4	3.6	3.8
2	3.4	4.2	4.0
Delta	1	0.6	0.2
Rank	1	2	3

According to the previous studies and considering the number of factors and levels for each factor, the L4 orthogonal array experiment design was used. It facilitates three factors with two levels for each factor with no interaction among factors. The response was collected from perceptions of 10 XYZ customers based on the combination of proposed improvement items through a questionnaire with a Likert scale using purposive sampling strategy. With a range of 1 (the smallest) and 5 (the highest), the average response was measured. It was then followed by the calculation of the difference between level 1 and 2 average score for each Taguchi Factor (i.e. A, B, and C). The higher the delta reflects the more important the Taguchi factor is. In this study, Taguchi factor A was deemed to be critical and very important. The more significant (larger), the better signal-to-noise ratio (S/N ratio) was utilized to test the result (Hartono 2020c). The response table for means and response table for the signal-to-noise ratios are shown in Tables 7 and 8 and followed by Figures 7 and 8.

It was found that the Taguchi factor A was the most critical compared to B or C, as it had the highest delta between the mean S/N ratio of that levels 1 and 2. The proposed combined

Table 8. Response table for signal to noise ratios (S/N ratios) with larger is better.

Level	A	B	C
1	12.83	11.07	11.58
2	10.61	12.38	11.86
Delta	2.22	1.30	0.28
Rank	1	2	3

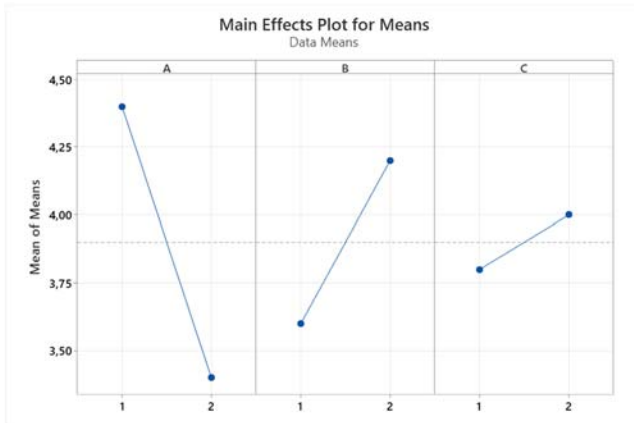

Figure 7. Main effects plot for means.

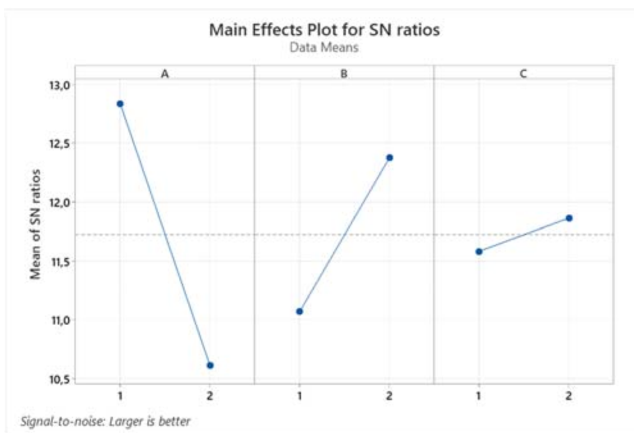

Figure 8. Main effects plot for SN ratios.

improvement strategies incorporating the response of each factor and level were A1 (Providing a picture of a map through a Quick Response (QR) scan), B2 (Providing an AR-based location map at each animal attraction spot), and C2 (Setting up a fixed picture of the map).

7. Discussion

This study shows the refined Kansei Engineering (KE) methodology incorporating SERVQUAL, Kano categorization, mining process, and Taguchi method for the more representative Kansei meaning and robustness of proposed solutions. In general, KE is positioned to be a method to match the customer's emotional needs (Kansei) with the properties of a product or service.

Nowadays, the challenge is getting more representative Kansei words (emotional needs) and robust improvement strategies. Therefore, more reliable, more long-lasting solutions are highly expected. Product or service offerings should be designed to fulfill customer needs and satisfaction, especially their emotional needs (Hartono 2020a). Thus, comparing existing products/services with their competitors in terms of functionality and usability is supposed to be insufficient unless it extends to more emotion-focused features.

Kansei is ideally unique. It is found in the outer and inner layers of customer needs, both verbally and non-verbally. What will be found in the inner layer of customer needs refers to hidden/latent/unspoken needs. They are related to emotional needs and are believed to be a challenge for innovation. It is a big challenge for designers to capture promptly what lies in the inner customer's mind, though the customers do not outspokenly express it.

This study highlights the critical critics regarding the more representative Kansei for current and future states. Thus, Kansei mining has been proposed. Kansei is not just discussing current-state emotional needs and responses of customers. It ideally refers to future-state psychological feelings of customer and user due to product and service interactions. Kansei is considered to be very important as it is one of the kinds of literature discussing the emotions and feelings of customers required for product design and development, service design and innovation, and understanding customers better for marketing purposes.

The more human senses are influenced, the more influential Kansei is. Also, the service attributes related to that Kansei are considered highly critical. According to Nagamachi (1995), during the service design, three states of affect will be included: visual perception, subjective impression, and emotional response. Inherently, Kansei is potentially captured by five basic human senses (i.e. sight, smell, hearing, touch, and taste). Among those five senses, sight is deemed to be the most dominant. It is about 70% of information sensed by sight. Again, Kansei captured by the human senses is a function of perceived service attributes and characteristics. In other words, what is expected, processed, and perceived by human Kansei will be translated into perceptual service design elements.

Afterward, it will be transferred to the designer's point of view. Most probably, the designer has no underlying clues regarding what the customer's Kansei is. Hence, mapping out the relationship between customer Kansei and design characteristics concerning the minimum discrepancy between customer and designer perception is quite critical. However, due to complex problems and contexts, Kansei's words sometimes were found to be fuzzy, ambiguous, and inconsistent. They lead to unclear meanings and are only short-term. The ideal expected condition is that the user or customer always provides consistent Kansei words. The obstruction of the ideal condition is potentially caused by the customer's mood and psychological condition apart from the stimulus of specific service experiences and interactions. For instance, when the customer is emotionally stable, he or she will give more reasonable Kansei due to a particular service experience. Again, this will be different as well when the service experience is intensively and extensively improved and different according to the function of time. One possible way to maintain the more reasonable and acceptable Kansei is the collection of Kansei using a more structured method involving more samples. In addition, through online sources using social media tweets, the collection of Kansei becomes more acceptable and convergent. Hence, Kansei mining is quite reasonably utilized. Kansei mining provides a decision- supporting procedure utilizing a set of historical data.

From the empirical study, ten settled Kansei words represented more stable emotional needs and impressions of customers in the zoo services. All 10 Kansei words were vital as they had an average important score above 4.00 out of 5.00. Kansei's 'awesome' was the most critical one as it had the lowest Kansei gap. It means that the Kansei had relatively high importance and response scores. It is reasonable and understandable as a zoo is an exciting and delightful place that can bring families together. Awesomeness refers to the variety of animals, especially those close to extinction. Therefore, a set of 10 Kansei words was deemed settled, solid, and representative due to zoo service experience.

More methods and approaches used in the KE methodology are essential in evaluating the current condition of service experiences and the appropriateness and robustness of proposed solutions. Previous studies discussed the application of KE incorporating service quality tools such as the Kano model and Quality Function Deployment (QFD) and also the Theory of Inventive Problem Solving (TIPS/TRIZ) (Hartono 2020c). However, the robustness of the proposed solutions is questionable.

The validity period of the solution tends to be not durable. It lasts briefly. In other words, the initial formalized solutions will be compassionate due to noise factors such as dynamics of customer expectation, field condition, or equipment. Here, in the zoo service experience, noise factors refer to, for instance, ambient temperature and humidity in the park and the number of visitors. Moreover, ideas for improvement mostly come from the designer's point of view instead of those from various stakeholders. As a consequence, it leads to a wider gap between what expected by the customer and perceived by the designer is. So what applies now will not be the same as what applies later. So it can be in days or months.

A study on the robustness of service design, development, and improvement strategies is quite promising. It is a significant gap in the research field in the area of services. Taguchi method has been used to generate and test the robustness of product and service parameter settings. Nevertheless, considering the flexibility of KE methodology, the study of the integration of Taguchi and KE is fascinating and still rare. It is offered that KE methodology engaged with robust-based solution and mining process is quite promising.

Regarding the case of zoo services, the prioritized problem will be followed up through a 2-stage process incorporating more robust-based solutions. Traditionally, the 'direction – clear road direction' as the most prioritized service attribute will be solved by a one-step solution such as the 'provision of visual-based information with fewer wordings'. However, potentially, there might be a less detailed and unrobust solution. Thus, this study proposes a 2-stage idea generation for a more robust solution. Here, the 'provision of visual-based information with fewer wordings' will be explored and narrowed down to 2-level factors through the Taguchi method. Then, it was deployed into: (1) Providing a picture of a map through Quick Response (QR) scan, and (2) Providing a physical picture of a map through hardcopy (paper-based). This 2-level factors step is expected to promote more detailed and robust design elements. Practically, the finding of this study will be helpful for zoo service managers as practical guidance for continuous improvement focusing on sensitive and critical customer Kansei.

This study contributes to the ergonomics literature in three ways. First, Kansei Engineering (KE) proposes a valuable knowledge on the importance of emotional and affective factors in human-service interaction. This is a complement to the human cognitive aspect in human-service experience. It is emotional aspect, apart from the rational one. KE is deemed to enhance service usability, perception, and satisfaction leading to improved customer experience and market competitiveness. Inherently, these are the key contributions of KE in ergonomics literature. It emphasizes user experience and goes beyond the traditional ergonomic approach which mainly focusing on anthropometric physical comfort and productivity. It supports more human-centred design in terms of emotions and customer feelings should be the central to the service design and innovation. Second, KE proposes a structured methodology for service design and development by capturing, translating, and analysing customer emotions and feelings in a more objective approach. Third, regarding more robust service design solution, KE is potentially being integrated with robust design methodology. In terms of ergonomics perspective, by combining KE and robust design, service designers not only can perform well in usability and functionality, but also evoke positive affect (Kansei). Eventually, this approach will enhance customer positive perception, expectation, and delight.

In the Artificial Intelligence (AI) era nowadays, how to identify and generate the pattern of customer emotions through big data collected is a big challenge and opportunity. It is both concerning and promising area for researcher and practitioner in the area of human emotional-based service design, innovation, and experience. Once the patterns of emotion generated through analysing vast amounts of customer data, it leads to personalized emotional experiences. As a potential consequence, this can enhance customer engagement better by tailoring services and their attributes to individual Kansei preferences. Moreover, the AI can emotionally leverage big data in gaining insights into how different customer segments respond to diverse stimuli emotionally. It is relevant to the fact that different cultural backgrounds or demographics will evoke different Kansei at a certain service context. Practically, it contributes a knowledge which can help providers and designers creating services that evoke specific emotions, leading to a deeper layer of emotional connection with users and customers. Big data analytics can potentially as well enable the AI systems to dynamically adjust the users' Kansei in real time and automatically interpret customer feedback, sentiment, and reviews. It will boost more efficient and prompt response to real-time user emotional states (including voice tone, facial expression, and behavioural patterns) so that more engaging and empathetic interaction with the user and customers is highly expected.

8. Conclusion and further research

This study offers a refined comprehensive framework of KE methodology incorporating an online review of Kansei mining and a robust design approach. It highlights how to collect better and more representative Kansei words and service attributes through a sentiment analysis approach. A case study on tourism attraction services (i.e. zoo) has been conducted to test the proposed applicative model of KE with an online review methodology incorporating the robust design. This research has some limitations. The first limitation is the relatively small number of samples. Regarding the generation of ideas in the Taguchi method, the second one concerns the representative factors leading to robustness. However, due to Kansei dynamics and various services, this integrated framework of refined KE with an online review methodology for robust service design can be tested in different service settings with the advancement of AI.

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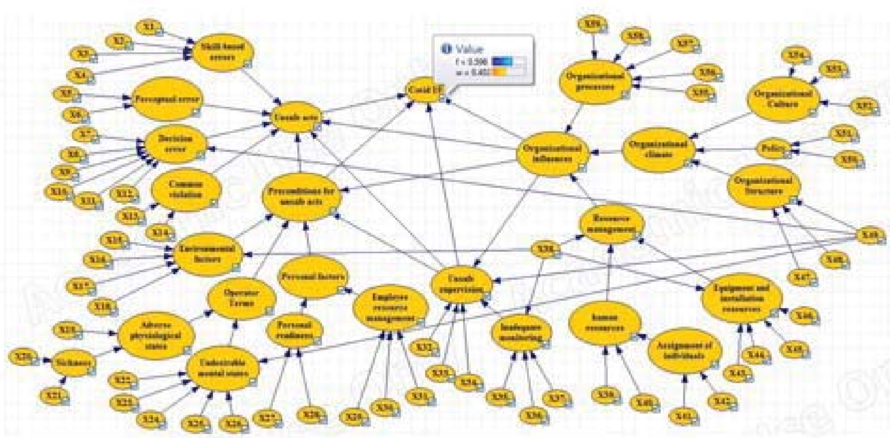

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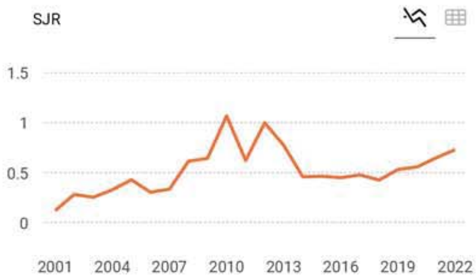

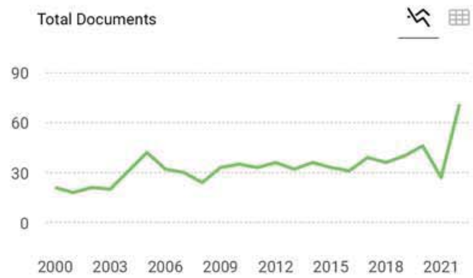

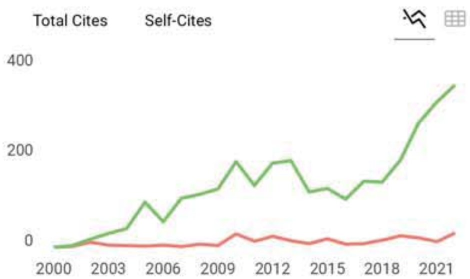

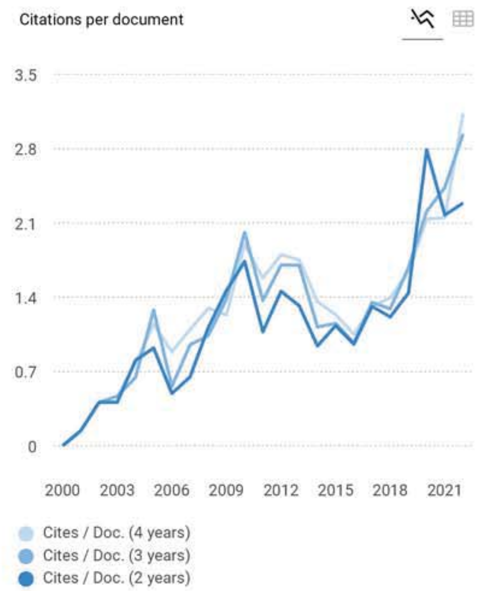

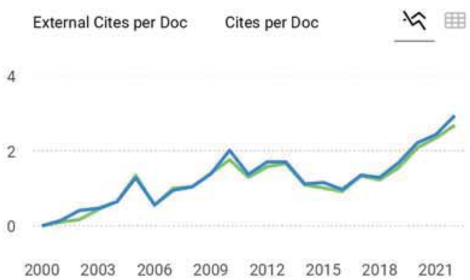

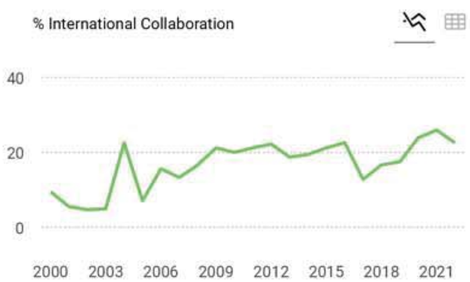

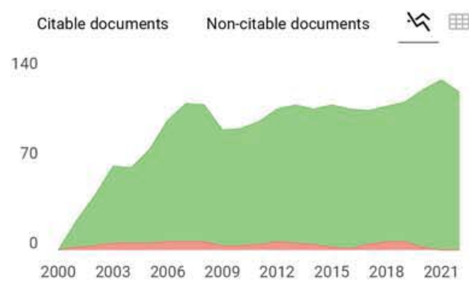

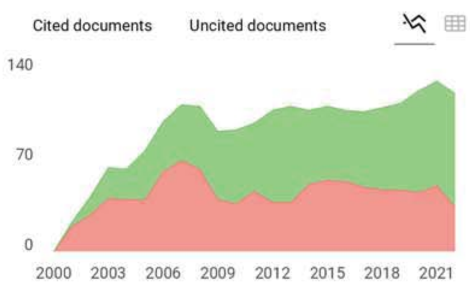

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Dear Melanie,
Thank you for your reply. The problem is resolved and I am pleased to report that my paper has been accepted for publication in "Theoretical Issues in Ergonomics Science"
Thanks again

reply

H **Hela MOURALI** 3 years ago

I have submitted a paper on Agust 19th 2019 but I have not received any information about it. Tracking system notes that the papaer is under review

reply

SCImago Team

Melanie Ortiz 3 years ago

Dear Hela,
thank you for contacting us.
Unfortunately, we cannot help you with your request, we suggest you contact the journal's editorial staff , so they could inform you more deeply.
Best Regards, SCImago Team

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