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A Bayesian based approach for analyzing customer's online sales data to identify weights of product attributes

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ABSTRACT

E-commerce websites include large volume of online customer data regarding customer preferences. This study puts forward a novel Bayesian methodology to estimate the impact of product attributes on customer satisfaction by analyzing online data, so that product designers and market researchers are facilitated in their decision making processes. This method proves that valuable information on customer insights can be provided even if we have only data of overall customer satisfaction score and product attribute characteristics. The unknown data are acquired via statistical methods such that non-parametric density estimation is utilized to estimate distributions of satisfaction scores of product attributes. The impacts of product attributes on customer satisfaction are considered as weights of mixture kernel distributions and posterior distributions of weights are simulated with Markov Chain Monte Carlo method. The applicability of the proposed methodology is demonstrated by a case study, in which online data of mobile phone market are analyzed.

1. Introduction

With the global health crises COVID – 19, the trend of online shopping has significantly increased. UN trade and development experts UNCTAD (2020) reported that the pandemic has led to sales growth of e-commerce websites by pointing out "dramatic" rise in online marketplace's share of all retail sales, from 16 per cent to 19 per cent in 2020. It is undeniable the fact that these web platforms are important source of information to the non-experienced customers, the market researchers, and the corresponding companies because most of the e-commerce websites enable the customers to express their satisfaction on webpages. In addition, several studies mentioned the significant influence of online evaluations on both product sales and customer's decision making processes (Chevalier & Mayzlin, 2006; Li & Hitt, 2008; Zhang, Ma, & Cartwright, 2013). Therefore, analyzing online ratings and reviews become more of an issue along with the change of human behaviors in shopping.

Analyzing customer opinions have been conducted by using several approaches such as interviews, phone surveys and questionnaire surveys. However, these traditional approaches are time-consuming and labor-intensive tools. Speaking of online customer opinion data, they are acquired with relatively less effort and necessitated less time in contrast with surveys. Moreover, customers are willing to express their opinions online, whereas it might be possible that customers reluctantly fill the survey forms (Groves, 2006). Due to these reasons, online customer data is a prevailing information source to understand customer satisfaction.

Customers post their evaluations on webpages with several ways such as numeric ratings and text reviews. In text reviews, customers can write their experiences on the products in free format, whereas they summarize their opinions by clicking a rate from predetermined numerical scale. Summary statistics of these ratings are displayed on webpages. Besides the text reviews, valuable information contained in online ratings cannot be negligible. Several studies indicate relationship between online ratings and customer satisfaction (Engler, Winter & Schulz, 2015; Gu & Ye, 2014; Thirumalai & Sinha, 2011). Numerical ratings have a big role on expressing customer satisfaction and thereby positive or negative impact on purchase decision of potential customers (De Maeyer, 2012). Product ratings enable to gain deeper understanding of pricing and quality decisions in supply chain (Wang, Leng, Song, Luo, & Hui, 2019) and of market outcomes such as price, demand, product sales and profits (Sun, 2012).

Online customer review characteristics have influence on customer

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choice. Kostyra, Reiner, Natter and Klapper (2016) revealed that the higher average rating leads to the higher choice probability. They also examined the importance of brand, price, and technical product attributes changes based on the presence of online customer ratings. Therefore, it is crucial to examine online ratings comprehensively.

Besides, some e-commerce web-sites such as Amazon, eBay etc. allow for rating to overall satisfaction of the product rather attribute specific rating. Even though some websites permit for attribute-specific evaluation, there might not sufficient data. Based on above-mentioned arguments, we aim at proposing novel methodology in deriving the impact of product attributes on customer satisfaction by analyzing online customer ratings. The overall product ratings and attribute characteristics are considered as inputs for the model, and the strength of each attribute on total satisfaction is calculated based on Bayesian approach.

The study proposes a methodology for extracting impact of product attributes on customer satisfaction, which also corresponds to a critical problem in multi-criteria decision making (MCDM) literature. This problem is determination of criterion weights. These weights to criteria have an important role for measuring overall preferences of alternatives. There are several approaches in determination of criterion weights in MCDM literature (Diakoulaki, Mavrotas, & Papayannakis, 1995; Wang, Jing, Zhang & Zhao, 2009; Zardari, Ahmed, Shirazi, & Yusop, 2015). However, the traditional approaches take into consideration performance score of each attribute in computational process, and they have weaknesses in reasoning under uncertainties. There is a research gap in determination of criterion weights for situations in which only overall satisfaction scores of alternatives are known. This study presents a new solution methodology in acquiring weights to criteria for MCDM analysis under uncertain environment via Bayesian inference. To the best of our knowledge, it is the first study extracting criterion weights only considering overall performance scores of alternatives based on kernel density estimation and Metropolis-Hastings algorithm. From the perspective of case study, the study fulfills the research gap in customer satisfaction literature with implementing the Bayesian solution in discovering impact of product attributes based on online data.

The significance of the research in terms of case study is twofold. The results can shed light on which attributes product designers on mobile phone market should concentrate to enhance product sale volumes as well as customer satisfaction. Analyzing online reviews are subject of computer science and engineering design literature as well as subject of business and marketing literature. For research perspective, this approach points out how deeper knowledge on customer preferences can be explored with relatively less data and computational effort. Although the proposed methodology is implemented in online data, it can also be applied to other decision making problems in which only overall satisfaction scores of alternatives are known.

The rest of this article is organized as follows. Related works are mentioned in Section 2. Section 3 introduces methods and basic concepts needed afterwards. Section 4 describes the problem and gives notations. Section 5 explains details of the proposed approach. Section 6 proposes case study of analyzing the impact of mobile phone attributes on overall customer satisfaction expressed with online ratings. Section 7 discusses the results and Section 8 presents comparison analysis. Finally, Section 9 provides conclusions and practical implications.

2. Related works

Customer satisfaction is crucial determinant of customer loyalty (Deng, Lu, Wei, & Zhang, 2010) and of purchase intention (Dash, Kiefer, & Paul, 2021) such that increase in customer satisfaction brings about increase in customer loyalty and product sales. Customer satisfaction is referred as one of the results of relational marketing and is a long-term phenomenon, not an abstract and event-oriented result (Lin, 2013). It leads to repurchasing and making recommendation to potential customers. Maintaining an old customer is more cost-effective than developing a new customer. Therefore, it is of significant importance for companies to systematically measure customer satisfaction and thereby get rational insight on customer opinions in both enhancing customer royalty and improving product sales.

Customer satisfaction can be measured through online data or customer surveys leading to the companies in product design and marketing (Chiu, Cheng, Yen, & Hu; 2011; Hou, Yannou, Leroy, & Poirson, 2019). It is crucial to explore to what extent each product attribute has impact on customer satisfaction (Wang, Lu, & Tan, 2018). There are several studies analyzing the impact of product attributes on overall customer satisfaction based on both conventional techniques such as surveys and relatively new techniques on analyzing online reviews. For instance, Farooq, Salam, Fayolle, Jaafar, and Ayupp (2018) revealed service quality dimensions such as airline tangibles, terminal tangibles, personnel services, empathy and image to have a significant impact on customer satisfaction of Malaysia Airlines by conducting a questionnaire survey. Ahmad et al. (2012) proposed rule-based method to analyze data features regarding various characteristics of customer satisfaction, in which rules are derived by using a probabilistic feature-selection technique. Imtiaz and Ben Islam (2020) analyzed product reviews on mobile phones based on sentiment analyses to identify how product attributes effect on customer satisfaction. Chen, Jin, Zhao, and Ji (2020) proposed a hierarchical Bayesian model to investigate how consumers differ geographically in terms of their preferences in purchasing mobile phones analyzing online reviews. Chen and Xu (2017) proposed a methodology in discovering most influential aspects of overall ratings based on product ontology, topic modeling and regression analysis. In that study, product ontology and Latent Dirichlet Allocation methods are made use of specifying product aspects. Polarity scores of these aspects are determined by conducting sentiment analysis. Finally, each aspect's impact on overall ratings is obtained based on multiple regression analysis. The proposed method is implemented into online data regarding single lens reflex camera, and most dominant aspects of product on customer satisfaction are revealed as cost performance, image quality and product integrity. Peláez, Cabrera, and Vargas (2018) developed an approach to extract the importance of consumer purchasing criteria based on sentiment analysis and Choquet integral.

Some studies focus on product design processes based on online data. Jin, Ji, & Liu (2014) prioritized engineering characteristics in quality function deployment based on online reviews by proposing integer mathematical model. Wang et al (2018) proposed logistic regression model to estimate the impact of product attributes on customer satisfaction scores. They analyzed the online reviews of washing machines by employing Latent Dirichlet Allocation to explore significant product attributes, and investigated the differences of customer satisfaction to the price level of washing machines. Kim and Noh (2019) made use of factor analysis and text analysis in finding the major factors pertaining to washing machine design, and they performed linear regression to estimate the influence of each factor to customer satisfaction.

Apart from evaluations of products, some studies evaluate online merchants' performances. Qu, Zhang, and Li (2008) implemented content analysis and regression analysis to determine the most important factors that affect the overall rating of online merchants. They point out that consumers give more importance to post-transaction services than online transaction services when they rate online merchants' performance in Yahoo's merchant review system. This study can assist online merchants to enhance their services and gain competitive advantages in electronic markets by revealing the weights customers put on criteria. Denguir-Rekik, Montmain, and Mauris (2009) proposed a system of multi-criteria evaluation of e-commerces based on a possibilistic framework to obtain the impact of variability and the divergence of customers' evaluations labeled by star scores regarding each criterion to the global evaluation.

In the present study, we focus on online product ratings. The proposed method puts forward an efficient and practical way to discover influence of product attribute on overall customer satisfaction. It differentiates from previous researches in terms of utilized methods. The satisfaction scores of product attributes are regarded as random variables whose probability distributions are estimated by utilizing non-parametric methods, namely kernel density estimation and impacts of product attributes are regarded as mixing proportions (weights) of mixture distributions whose posterior distributions are simulated via Metropolis-Hasting algorithm. Thereby, both strengths of product attributes on customer satisfaction and satisfaction scores of product attributes are represented with random variables instead of scalar values, and they include more information according to a scalar value. In addition, Bayesian inference algorithm enables to update posterior distributions of weights together with gaining new information on weights. Furthermore, this method contains a clear logic and a simple computational process.

In the literature, Huang, Pahwa and Kong (2012) made use of kernel density estimation and MCMC for proposing yield based process capability indices. The distribution function of quality characteristic is obtained via Kernel density estimation. Metropolis-Hastings algorithm is used for sampling from the estimated density. Process capability indices are calculated by counting the nonconforming M-H samples. We utilize kernel density estimation and MCMC like Huang, Pahwa and Kong (2012). However, there are some differences both in focus of problem and general methodology. For instance, mixture proportions of mixture kernel functions are estimated via MCMC sampling in our study. The estimated mixture proportions are random variables displayed with histograms. The process capability indices in Pahwa and Kong (2012) are real numbers obtained with an equation whose inputs are retrieved from M-H samples. Our study generates a new and effective solution methodology for the problem, which is the estimation of product feature weights (impact) on customer satisfaction in uncertain environment; the present approach can also be related to the weight determination problem in the MCDM. Attribute weights are important component in MCDM analysis, because weights play an important role in result of analysis and weights can change ranking of alternatives. Several methods have been proposed for attribute weight determination, which can be grouped into subjective, objective and hybrid methods. Pena et al. (2020) and Pena et al. (2021) reviewed the weighting methods and proposed a taxonomy. The preference of the weighting method in MCDM analysis is related to circumstances such as the availability of data, specifications of experts and the considered decision-making problem. According to the traditional classification, the relative importance of each criterion is acquired based on the analyst's subjective evaluation in subjective methods. For instance, Analytical Hierarchy Process (AHP) is one of the most common subjective weighting methods based on pairwise comparisons between the criteria (Saaty, 2003). However, objective weighting methods extract the weights from data based on mathematical models without querying the decision makers or analysts. Entropy method (Deng, Yeh, & Willis, 2000), the Correlation Coefficient and Standard Deviation methods (Wang & Luo, 2010) and the Criteria Importance through Inter-criteria Correlation, namely, CRITIC (Diakoulaki et al., 1995) are the most widely used objective weighting methods. The performance scores of attributes are given in decision matrices in all of the above-mentioned methods. These methods are incapable of extracting the weights from insufficient data, and they can only deliver deterministic weights. However, the proposed method enables researchers to extract weights based only on overall performance scores and can cope with uncertainties by presenting stochastic weights.

In addition, there are few studies that integrate some famous theories regarding customer satisfaction and MCDM methods in the literature. Kano model is one of the famous theories related to customer satisfaction, which categorizes the attributes of a product or service based on how well they can satisfy customer needs. Ghorbani, Mohammad Arabzad, and Shahin (2013) deal with the supplier selection problem characterized as the MCDM problem, in which the importance weights of criteria are calculated based on fuzzy Kano questionnaire and fuzzy analytical hierarchy process. Kano model categories the criteria in five types of quality attribute. AHP plays the main role in criteria weighting. Our study purposes to estimate the weights of product attributes on aggregated customer satisfaction scores having been presented on online platforms. Customer satisfaction modeling or measurement is not within the scope of this work. Customer satisfactions are already available as online product ratings. The research question is what the weight of each product attribute in these aggregated customer satisfaction scores is. Estimating the impact of product attributes on customer satisfaction points out this question in this study.

3. Theoretical background

In this section, we explain methods and concepts employed in the proposed methodology. Markov Chain Monte Carlo (MCMC), a fundamental method used in Bayesian inference, is illustrated at first, and then Dirichlet distribution is addressed, which is one of the most common prior distributions used in this field. Finally, Kernel density estimation method is explained.

3.1. Markov chain Monte Carlo methods

Monte Carlo integration draws samples from the desired distribution, and then forms sample averages to approximate expectations. MCMC draws these samples by running a cleverly constructed Markov chain for a long time (Gilks, Richardson, & Spiegelhalter, 1995).

MCMC applications are generated mostly for Bayesian inference. In Bayesian inference, we can encounter computations of posterior distributions, which often require solutions of complex integrals. In such circumstances, MCMC is used as an approximation approach to estimate posterior distributions and complex integrals.

There are various types of MCMC algorithms, one of which is Metropolis-Hasting algorithm that was developed by Metropolis et al. (1953). This algorithm constructs a Markov chain of which stationary distribution is $\pi(x)$. **Algorithm 1** describes Metropolis-Hasting algorithm providing steps to reach of the desired distribution. According to the algorithm, the first step is generating sample point x^* from proposal distribution $q(.|x^{(t)})$, then it must be checked whether the sample point generated is accepted for the next state of $x^{(t+1)}$. Therefore, the acceptance probability is calculated. If acceptance probability is higher than a random number drawn from uniform distribution, the next step becomes $x^{(t+1)} = x^*$; otherwise the next step in the chain is as the previous one.

Algorithm 1: Metropolis-Hasting algorithm

Initialise $x^{(0)}$; set $t = 0$
For $t = 0$ to $N-1$
  Sample a point x^* from $q(.|x^{(t)})$
  Sample a random variable u *Uniform*$(0,1)$
  Calculate the acceptance probability:
  $$R(x^*, x^{(t)}) = \min\left\{1, \frac{\pi(x^*)q(x^{(t)}|x^*)}{\pi(x^{(t)})q(x^*|x^{(t)})}\right\}$$
  If $u < \alpha$
    $x^{(t+1)} = x^*$
  else
    $x^{(t+1)} = x^{(t)}$
  end
end

3.2. Dirichlet distribution

Dirichlet distribution is a multivariate generalization of the beta distribution, whose support includes k-dimensional vectors of which each member is a real number interval zero and one, and sum of the members equals to one. The joint distribution function of a random vector $w_j = (w_1, w_2, \cdots, w_k)$ following Dirichlet distribution is.

$$f(w_1, w_2, \cdots, w_k; \alpha_1, \alpha_2, \cdots, \alpha_k) = \frac{\Gamma(\alpha_1 + \cdots + \alpha_k)}{\Gamma(\alpha_1)\cdots\Gamma(\alpha_k)} \prod_{j=1}^{k} w_j^{\alpha_j - 1},$$

where $\sum_{j=1}^{k} w_j = 1$, $w_j \geq 0$ for $\forall j$, and $\Gamma()$ is gamma function (Giudici, Givens, & Mallick, 2013).

It is not possible to draw sample from this distribution directly. There are two standard approaches for sampling. In order to sample a random weight vector $w_j = (w_1, w_2, \cdots, w_k)$ from the k-dimensional Dirichlet distribution with parameters $(\alpha_1, \alpha_2, \cdots, \alpha_k)$, we utilize the fastest approach (Gelman, Carlin, Stern, Dunson, Vehtari, & Rubin, 2013). That is, we draw k independent random samples $(x_1, x_2, \cdots, x_k)$ from gamma distributions each with probability density in Eq. (1)

$$x_j \sim Gamma(\alpha_i, 1) = \frac{x_j^{\alpha_i - 1} e^{-x_j}}{\Gamma(\alpha_j)}, \tag{1}$$

where $\Gamma(.)$ is gamma function, and then normalize the samples by $w_j = x_j / \sum_{j=1}^{k} x_j$.

3.3. Kernel density estimation

There are two approaches to estimate probability distribution function of the observed data which are parametric and non-parametric (Silverman, 2018). Parametric approach assumes that the observed data are drawn from a known distribution and estimates the parameters of the distribution from data. Otherwise, non-parametric approach estimates density function based on data. Kernel density estimation is one of the non-parametric approaches. Consider n independent and identically distributed samples $X_1, \cdots, X_n$ drawn from a univariate distribution with unknown density f. This non-parametric approach estimates unknown density function using kernel density estimator denoted by $\hat{f}$ in Eq. (2).

$$\hat{f}(x) = \frac{1}{nh} \sum_{i=1}^{n} K\left(\frac{x - X_i}{h}\right) \tag{2}$$

where h is smoothing parameter (bandwidth) and K is non-negative kernel function.

There are various kernels in literature (Härdle, 1991). Different kernels generate different shapes of densities. The most common kernel functions are Uniform, Epanechnikov quadratic, Triweight and Gaussian kernels proposed with Eq. (3)–(6). The main difference of Gaussian kernel is that its support is real numbers, whereas the supports of the others are restricted. However, kernel choice is less important than bandwidth (Silverman, 2018).

Uniform kernel:

$$K\left(\frac{x - X_i}{h}\right) = \begin{cases} 0.5 & \text{if} \left|\frac{x - X_i}{h}\right| \leq 1 \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

Epanechnikov quadratic kernel:

$$K\left(\frac{x - X_i}{h}\right) = \begin{cases} 0.75^* \left(1 - \left(\frac{x - X_i}{h}\right)^2\right) & \text{if} \left|\frac{x - X_i}{h}\right| \leq 1 \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

Triweight kernel:

$$K\left(\frac{x - X_i}{h}\right) = \begin{cases} \frac{35}{32}^* \left(1 - \left(\frac{x - X_i}{h}\right)^2\right)^3 & \text{if} \left|\frac{x - X_i}{h}\right| \leq 1 \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

Gaussian kernel:

$$K\left(\frac{x - X_i}{h}\right) = \frac{1}{\sqrt{2\pi}h} e^{\left(-\frac{(x - X_j)^2}{2h^2}\right)} \tag{6}$$

Bandwidth has influence on estimator such that it controls degree of smoothing. Bandwidth can be determined with subjectively as well as using data based selection procedures (Silverman, 2018).

4. Problem description

There are vast numbers of customer ratings regarding products sold in e-commerce websites. This article aims to explore how much importance the customers give to each attribute of the sold product by mining these customer ratings. The concerned problem can be defined as determining the impact of product attributes on customer satisfaction based on online product ratings. Consider that a researcher is responsible for examining a product such as mobile phone, laptop, camera etc. sold in e-commerce website. Information regarding product attributes on all of brands and models of this product can be found in the website. In addition, this website allows for the customers to declare their satisfaction with the product by rating. To assist this analysis, the proposed methodology can give a support in exploring on which characteristic of the product customers put more weight through overall satisfaction scores. Based on the result of the analysis, companies manufacturing this product give more importance to this attribute in designing phase. According to marketing perspective, companies highlight this attribute of the product in advertising to attract new customers.

The notations with their implications are introduced as below, which represent the sets and variables used in the proposed methodology.

- $P = \{P_1, P_2, \cdots, P_m\}$: a set of products with customer ratings sold in e-commerce website, where P_i indicates ith product. The expression 'product' indicates any brand or model hereafter.
- $A = \{A_1, A_2, \cdots, A_k\}$: a set of attributes of the product, where A_j indicates the jth attribute.
- $C_j = \{C_{j1}, C_{j2}, \cdots, C_{jn_j}\}$: a collection of categories of jth attribute created after discretization, where n_j denotes the number of categories of the jth attribute.
- A_{ij}: indicates category of attribute A_j belonging to product P_i and $A_{ij} \in C_j$.
- $W = \{w_1, w_2, \cdots, w_k\}$: vector of weights of attributes, where w_j indicates the weight of jth attribute with the constraint that $w_j > 0$ and $\sum_{j=1}^{k} w_j = 1$.
- z_i: overall score of product P_i, $i = 1, 2, \cdots, m$. Each value z_i is a member of the set Z.
- t_j: indicates a value of product attribute A_j taken by any product P_i in database (i.e., 6.4 in. for screen size).
- Y_{ij}: random variable denotes satisfaction score of product P_i with reference to attribute A_j, and y_{ij} indicates the realization of random variable Y_{ij}.
- $f(Y_{ij} = y_{ij})$: distribution function of random variable Y_{ij}.

5. Methodology

In this section, we explain the proposed methodology. Fig. 1 gives solution procedure for the stated problem of determining the impact of product attributes on customer satisfaction based on online product ratings. The method mainly consists of two phases, namely data preparing and inference. Data preparing phase incudes three steps, which are crawling online product ratings, discretization and estimating kernel densities of satisfaction scores of products regarding attributes, respectively. Then, inference phase follows three steps which are obtaining mixtures of kernel densities, acquiring likelihood function via mixture densities and utilizing Bayesian inference algorithm to compute

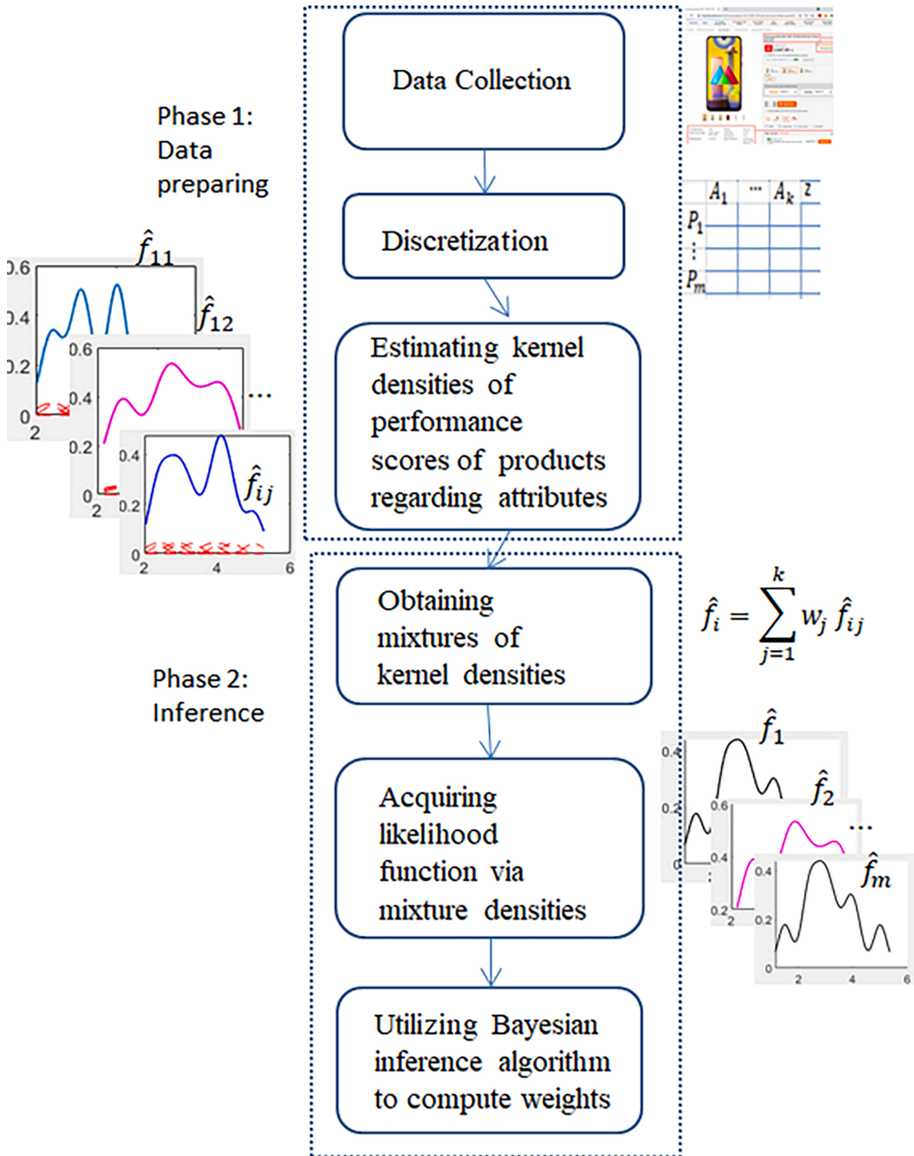

Fig. 1. Solution procedure for the problem of determining the impact of product attributes on customer satisfaction based on online ratings.

attribute weights, respectively.

5.1. Data preparing phase

The first step of data preparing is gathering the data consisting of characteristics of product attributes and overall numeric ratings. Data collection consists of three steps as shown in Fig. 2. Data collection process starts with making decisions on the product type and attributes to be analyzed, and on the web pages from which the data are collected. For instance, mobile phone is the product type addressed in this study. At the next step, a web crawling tool such as Octoparse is used for retrieving attribute information and overall product ratings on products from the web pages. The collected data is saved in a comma-separated values (CSV) file. At the last step, the appropriate products are filtered

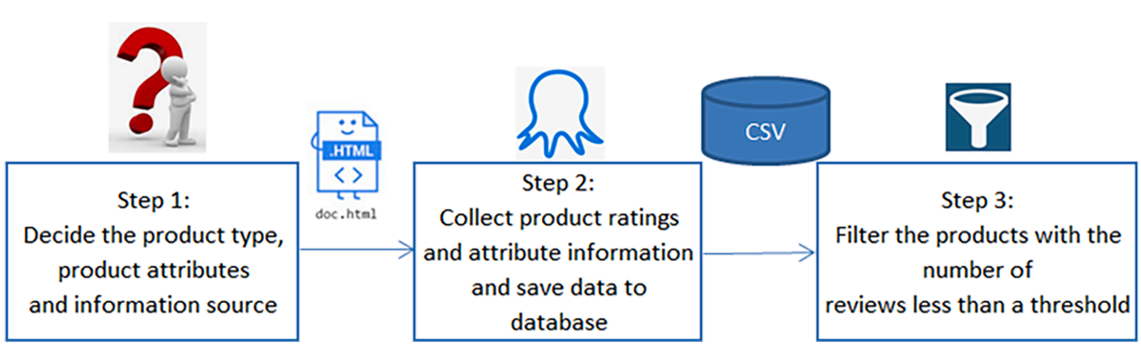

Fig. 2. Flowchart of data collection process.

for the analysis. In this study, the mobile phones with at least 50 reviews are used for the analysis.

Two types of product attributes are concerned, namely categorical attributes and continuous attributes. For instance, memory is a categorical attribute for product of mobile phone, which takes a value from a set with relatively less members such as $C_3 = \{8, 16, 32, 64, 128, 256, 512\}$. On the other hand, Battery power is a continuous attribute, which takes a value from an interval such as between 1560 and 7000 mAh. In order to discretize continuous attributes, we use equal width discretization, in which the number line between $\min(t_j)$ and $\max(t_j)$ are divided into predetermined number of equal widths (Dougherty, Kohavi, & Sahami, 1995). For a detailed explanation, consider the Eq. (7) where each function $f_j : \mathbb{R} \rightarrow \{C_{j1}, C_{j2}, \cdots, C_{jn_j}\}$ transforms the value of t_j into categorical symbol.

$$f_j(t) = \begin{cases} C_{j1}, min(t_j) \leq t < min(t_j) + wd_j \\ C_{j2}, min(t_j) + wd_j \leq t < \min(t_j) + 2{*}wd_j \\ \vdots \\ C_{jn_j}, min(t_j) + (n_j - 1){*}wd_j \leq t \leq max(t_j) \end{cases} \tag{7}$$

where $t \in t_j$, $wd_j = (\max(t_j) - \min(t_j)) / n_j$, and $j = 1, 2\cdots, k$.

After the discretization step, we illustrate data in Table 1. It displays overall score z_i of each product available in the website having been obtained by averaging all ratings for the product, as well as displays the categorical values denoted by A_{ij} ($A_{ij} \in C_j$).

We consider the satisfaction score of product P_i with reference to attribute A_j as a continuous random variable Y_{ij}. In order to acquire values of random variables Y_{ij}, the procedure considering overall scores z_i and categorical values A_{ij} are followed by using Eq. (8).

$$Y_{ij} = y_{ij},\ \ y_{ij} \subseteq Z,\ \ y_{ij} \ni z_r\ \ r\,|A_{ij} = A_{rj} \tag{8}$$

where $y_{ij} = \{y_{ij}^1, y_{ij}^2, \cdots y_{ij}^t, \cdots, y_{ij}^s\}$ denotes the set containing values of random variable Y_{ij} with s number of values and a value of random variable provides assignment of $y_{ij}^t = z_i$.

Another way to interpret the procedure is that, satisfaction scores of products with respect to attributes are represented by random variables whose values are extracted from overall scores such that the scores of products belonging to same category concerning an attribute are considered as observations of these random variables.

The distribution of Y_{ij} is computed by kernel density estimation approach (Giudici et al., 2013) which employs Eq. (9) to acquire the function fitted these values.

$$\hat{f}(Y_{ij}) = \frac{1}{sh} \sum_{t=1}^{s} K\left(\frac{Y_{ij} - y_{ij}^t}{h}\right) \tag{9}$$

where K is a kernel function and h is bandwidth. Kernel density estimation is performed with Gaussian, Uniform, Epanechnikov quadratic and Triweight kernel functions separately. For instance, kernel density estimation approach generates density distribution by averaging of s Gaussian functions with each value considered as a center with Eq. (10) when Gaussian kernel is used.

$$\hat{f}(Y_{ij}) = \frac{1}{s} \sum_{t=1}^{s} \frac{1}{\sqrt{2\pi}h} e^{\left(-\frac{\left(Y_{ij} - y_{ij}^t\right)^2}{2h^2}\right)} \tag{10}$$

Bandwidth is determined using rule of thumb, which gives optimum bandwidth $\hat{h}_o$ as $1.06\,\hat{\sigma} n^{-1/5}$ where n is number of observations and $\hat{\sigma}$ is estimator of standard deviation. For other non-Gaussian kernels, the equivalent bandwidth $\hat{h}_1$ is acquired by referencing normal density. The details for the calculus of bandwidth are given in (Härdle, 1991; Silverman, 2018).

The result of above-mentioned computation can be illustrated in Table 2.

5.2. Inference phase

After the marginal satisfaction scores are acquired, we suggest a relationship between these scores and corresponding overall scores such that it enables us to derive the importance weights of product attributes. The suggested relationship is to define overall satisfaction score of each product as an observation of random variable Z_i distributed with mixture density in Eq. (11):

$$Z_i \sim \sum_{j=1}^{k} w_j \hat{f}(Y_{ij} = z_i | i, j), \tag{11}$$

where w_j indicates the corresponding attribute weights with $w_j > 0$,and $\sum_{j=1}^{k} w_j = 1$.

The above-mentioned relationship is mixture of kernel distributions. Weighted sum of the marginal densities of attribute scores forms the mixture distribution of overall customer satisfaction score. The weight w_j indicates impact of product attribute A_j on overall rating score.

MCMC is utilized to obtain these weights, in other words, to sample from posterior distributions of weights. The attribute weights are assumed to lie on k-dimensional simplex, which is a space in R^k and any data point $w = (w_1, w_2, \cdots, w_k)$ satisfies the conditions that $w_j > 0$ and $\sum_{j=1}^{k} w_j = 1$. Dirichlet distribution is an appropriate distribution to express the attribute weights since it provides a sample vector whose elements sum to 1. Prior distribution of weight vector is derived from a Dirichlet distribution, and this distribution is also used as proposal to construct independence Markov chain. Consequently, Metropolis-hasting acceptance ratio equals the likelihood ratio in this MCMC algorithm (Giudici et al., 2013). The acceptance ratio is viewed in Eq. (12).

$$R(w^{(t)}, w^*) = \frac{L(w^* | z_1, \cdots, z_i, \cdots, z_m)}{L(w^{(t)} | z_1, \cdots, z_i, \cdots, z_m)} \tag{12}$$

where w is weight vector, z are observed data with likelihood function $L(w|z)$ for parameters w which have prior distribution $p(w)$. Meanwhile, likelihood of attribute weights is expressed with Eq. (13).

$$L(w | z_1, \cdots, z_i, \cdots, z_m) = \prod_{i=1}^{m} \sum_{j=1}^{k} w_j \hat{f}(Y_{ij} = z_i). \tag{13}$$

Table 1
Data matrix after discretization.

	Attribute (j)				Overall score
Product (i)	1	2	⋯	k	Z
1	A_{11}	A_{12}	⋯	A_{1k}	z_1
2	A_{21}	A_{22}	⋯	A_{2k}	z_2
⋮	⋮	⋮	⋮	⋮	⋮
m	A_{m1}	A_{m2}	⋯	A_{mk}	z_m

Table 2
Data matrix after density estimation.

P_i	Attributes				Overall score (z)
	A_1	A_2	⋯	A_k	
1	$\hat{f}(Y_{11} = y_{11})$	$\hat{f}(Y_{12} = y_{12})$	⋯	$\hat{f}(Y_{1k} = y_{1k})$	4.6
2	$\hat{f}(Y_{21} = y_{21})$	$\hat{f}(Y_{22} = y_{22})$	⋯	$\hat{f}(Y_{2k} = y_{2k})$	4.8
⋮	⋮	⋮	⋮	⋮	⋮
m	$\hat{f}(Y_{m1} = y_{m1})$	$\hat{f}(Y_{m2} = y_{m2})$	⋯	$\hat{f}(Y_{mk} = y_{mk})$	4.5

Logarithmic transformation is utilized for more rational computation, thereby product operator is converted to sum operator in Eq. (13). Acceptance probability is calculated according to logarithmic likelihoods. **Algorithm 2** presents the steps followed to obtain posterior distributions of attribute weights. In each iteration t, random value of vector w is proposed based on $Dirichlet(\alpha_1, \alpha_2, \cdots, \alpha_k)$, and the proposal is accepted considering acceptance probability and a uniformly distributed random number. Finally, they converge to a sample from $p(w|z)$ and weight vector $w = (w_1, w_2, \cdots, w_k)$ is explored.

Algorithm 2: MCMC algorithm for attribute weight inference

Initialise $w^{(0)}$; set $t = 0$
For $t = 0$ to $N-1$
  Sample a point w^* from $Dirichlet(\alpha_1, \alpha_2, \cdots, \alpha_k)$
  Sample a random variable u $Uniform(0,1)$
Calculate the acceptance probability:
$R(w^{(t)}, w^*) = \min\{1, \ln(L(w^*|z_1, \cdots, z_i, \cdots, z_m)) - \ln(L(w^{(t)}|z_1, \cdots, z_i, \cdots, z_m))\}$
  If $\ln(u) < R(w^{(t)}, w^*)$
    $w^{(t+1)} = w^*$
  else
    $w^{(t+1)} = w^{(t)}$
  end
end

6. Case study

In this section, we demonstrate how the proposed method is applied in exploring to what extent customers give importance to each technical attribute of the mobile phones sold in an e-commerce website of Hepsiburada (https://www.hepsiburada.com/). This website is one of the popular e-commerce website in Turkey, which allows their customers for posting their comments and ratings in the form of 1–5 star scale. We demonstrate the retrieved data by rectangle frames in Fig. 3. The product names, information regarding to product attributes, overall ratings and the number of reviews are gathered into a database via web scraping software, namely, Octoparse (https://www.octoparse.com/).

After discarding the products with less than 50 ratings, the database includes 163 products. The considered product attributes are A_1 (Screen size), A_2 (Camera resolution), A_3 (Memory), A_4 (Battery power). These attributes are chosen since they are among commonly mentioned attributes in the website. The details of the collected data regarding to mobile phones are shown in Table 3. This table includes some descriptive statistics of product attributes, overall ratings and the number of reviews. Graphical representations of dataset are displayed in Fig. 4. The variables except Memory are continuous. They are displayed via histograms with seven bins. The y-axes of the histograms give relative probabilities that are the ratio of the number of observations in the bins to the total number of elements in the input data. Some explanations from these figures are as follows. For instance, 32 % of the mobile phones have 64 GB memory. 47.2 % of the mobile phones have a screen size between 6.1 and 6.52 in. The camera resolutions of 52.7 % of the mobile phones are smaller than 24 MP. The percentage of the mobile phones with a battery size in the interval [3000 3800] mAh is 33. The higher percentages of the average online ratings are in the interval [4.45 4.7]. 75 % of the mobile phones have reviews between 50 and 460.

Table 3
Descriptive summary of the dataset.

Descriptive statistics		Mean	Standard deviation	Min	Max
Product attributes	Screen size (inch)	6.045	0.572	4	6.9
	Camera resolution (MP)	34.815	28.996	2	168
	Memory (GB)	81.128	63.671	8	512
	Battery (mAh)	3732.134	962.447	1560	7000
	Number of reviews	406.539	518.227	50	3193
Overall ratings	Average satisfaction scores	4.560	0.238	3.3	4.9

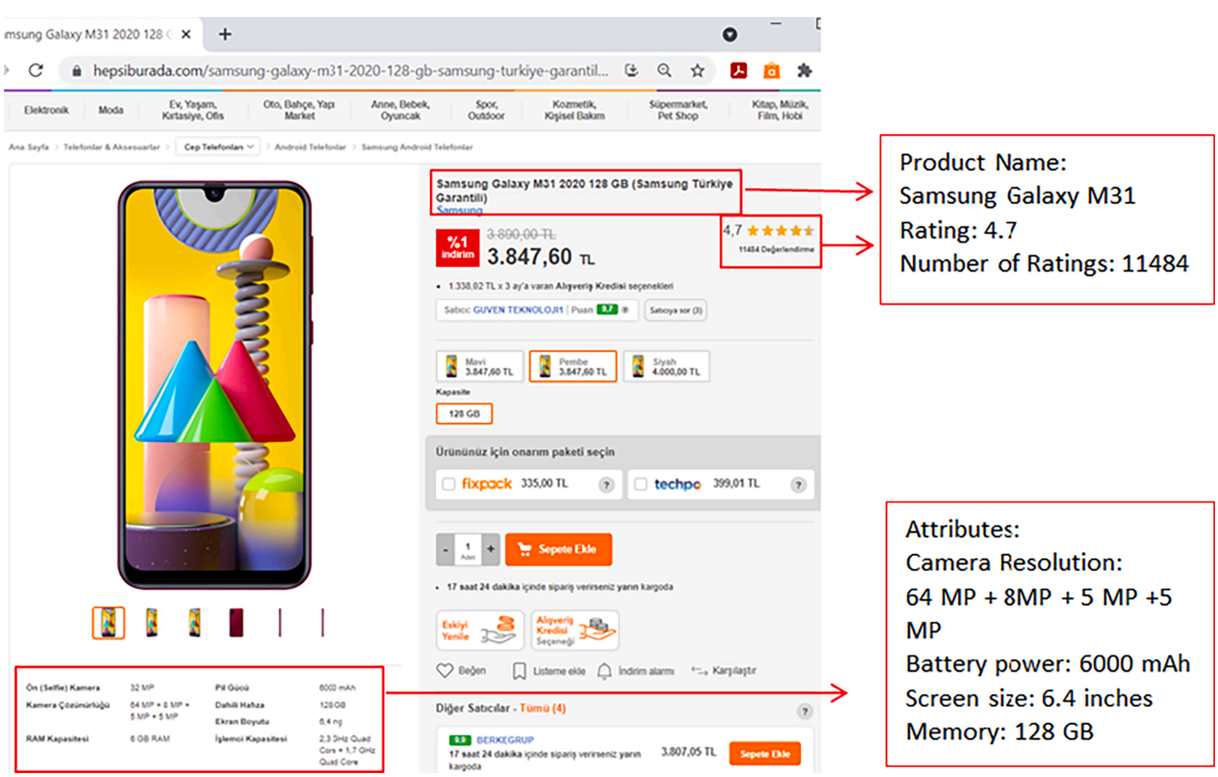

Fig. 3. Screenshot of e-commerce webpage on Hepsiburada.com.

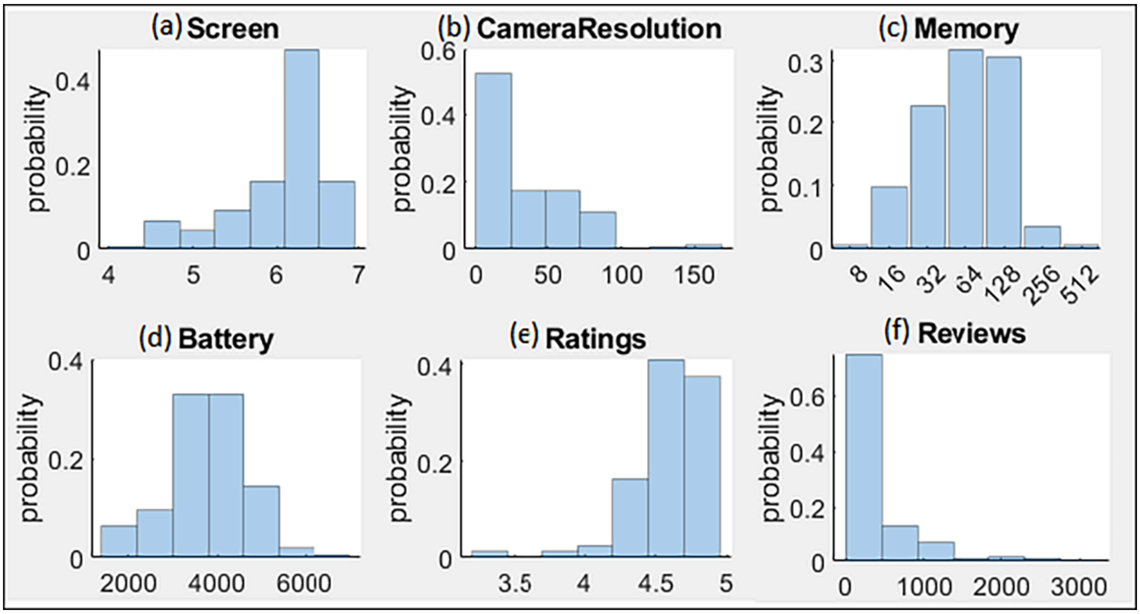

Fig. 4. Histograms of the variables of a)Screen size (inch), b) Camera Resolution (MP), c) Memory (GB), d) Battery (mAh), e) Average online ratings, and f) Number of reviews.

Since the attributes excluding Memory are continuous attributes, they are discretized by using Eq. (7). All attributes have seven categories of which logic is analogous with linguistic variables extremely low, very low, low, medium, high, very high, and extremely high, but indications are displayed by symbols in Table 4.

After estimating random variables and densities, we conduct MCMC algorithm for 10,000 iterations with the first 1000 iterations discarded as burn-in samples. We check the convergence by acquiring convergence parameter $\hat{R} = 1.00$ obtained for 10 chains. Meanwhile, we control efficient sample sizes and autocorrelation plots. Symmetric Dirichlect distribution whose parameters are taken the same value is determined as prior distribution of weight vector and value of 1 is assigned to concentration parameter α. This means that Dirichlet distribution becomes the uniform distribution over the simplex. Concentration parameter is determined as 1 when there is no prior knowledge on weight vector. According to presence of prior knowledge on weights, concentration parameter can be changed, and thereby different posterior distributions can be revealed.

7. Results of proposed method

The proposed method is coded in MATLAB by using a computer with i7-106567 processor number and 1.30 GHz CPU. Gaussian, Uniform, Epanechnikov quadratic and Triweight kernel functions are separately utilized while distributions of random variables are estimated. As the result of simulations, the posterior distributions of attribute weights are displayed in the following Figs. 5-8.

Posterior probability of order of attribute weights can be revealed by evaluating posterior sample values obtained from MCMC method (Musal, Soyer, McCabe, & Kharroubi, 2012). Table 5 shows some posterior probabilities regarding the order of weights with reference to different kernel functions. For instance, weight of A_4 (Battery) is higher than weight of Screen (A_1) at 67.6 percentages of simulated values with reference to Gaussian kernel. The order $w_2 \succ w_4 \succ w_3 \succ w_1$ is found at 26 percentages of simulated values, which is the highest proportion. The proportion rates of this ranking are the highest scores for the results with the other kernels as well. This ranking is found at 29.1 percentages of simulated values with Triweight kernel, at 28.3 percentages of simulated values with Epanechnikov quadratic kernel, and 28.8 percentages of simulated values with Uniform kernel functions. In evaluating these probabilities, it should be taken into account the fact that there are 24 combinations for order of four weights. Consequently, we deduce that the customers give more importance to Camera Resolution (A_2), whereas give less importance to Screen size (A_1) in evaluating a mobile phone.

Table 4
Result of discretization.

P_i	Attributes				Overall score (z)
	A_1	A_2	A_3	A_4	
1	C_{17}	C_{22}	256 GB	C_{44}	4.6
2	C_{17}	C_{24}	128 GB	C_{47}	4.8
3	C_{16}	C_{24}	128 GB	C_{46}	4.7
⋮	⋮	⋮	⋮	⋮	⋮
163	C_{16}	C_{22}	128 GB	C_{44}	4.5

8. Comparative study

In this section, comparisons regarding rankings are proposed and strengths of the method are explained. Nonlinear mathematical model, ordinary least squares (OLS) regression model and multilayer perceptron models are created. Fivefold cross validation is implemented for comparative study. This method splits data into five equal width folds. Four folds are trained to construct the model and the remained fold is used to test it. This process is repeated five times; thereby the average performance metrics of five models is taken. The performance metrics are mean squared error (MSE), root mean squared error (RMSE) and mean absolute percentage error (MAPE), which are presented in Eqs. (14)–(16).

$$MSE = \frac{\sum_{i=1}^{m}(z_i - \hat{z}_i)^2}{m} \tag{14}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{m}(z_i - \hat{z}_i)^2}{m}} \tag{15}$$

$$MAPE = 100^{*}\frac{1}{m}\sum_{i=1}^{m}\frac{|z_i - \hat{z}_i|}{z_i} \tag{16}$$

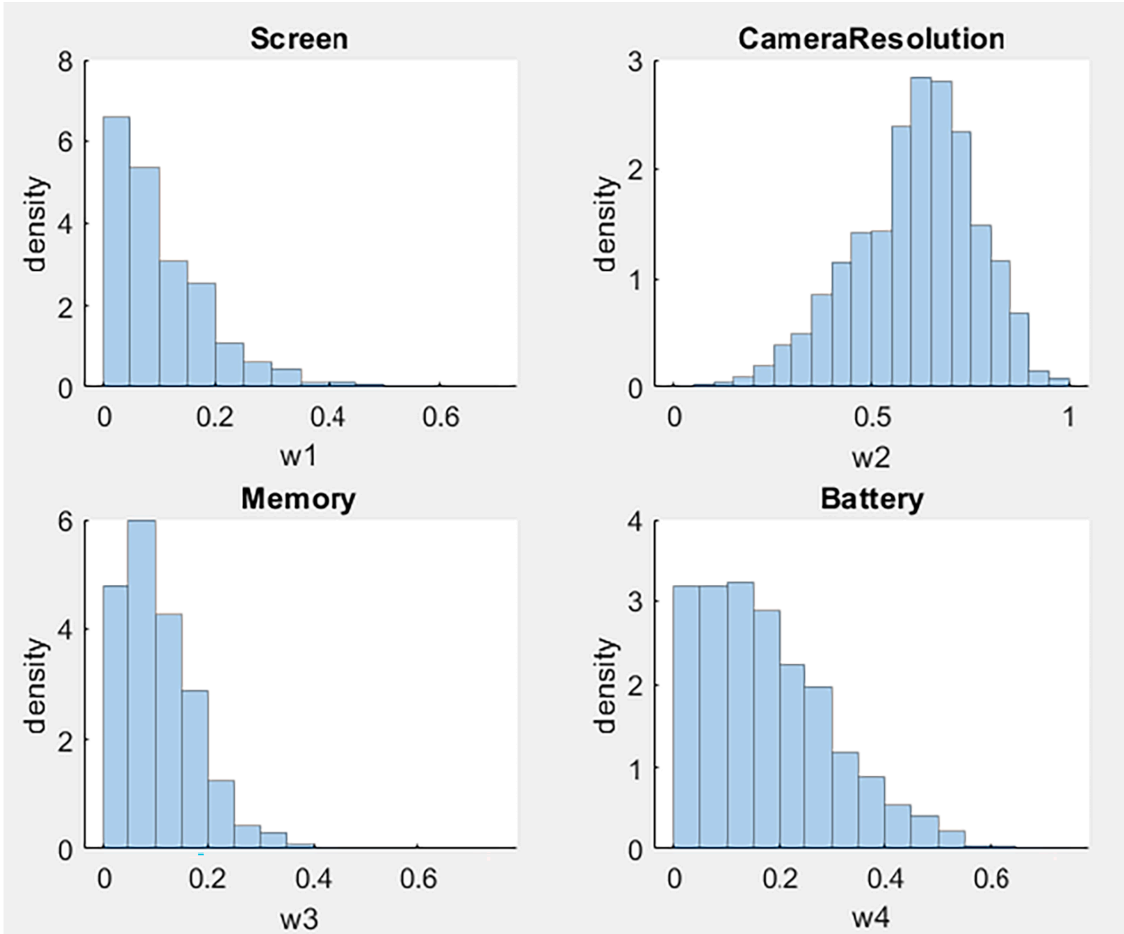

Fig. 5. Posterior probability distributions of weights with Gaussian kernel: $\overline{w} = [0.136, 0.497, 0.169, 0.196]$.

where $\widehat{z}_i$ is predicted overall satisfaction score of product, z_i is actual overall satisfaction score and m is the number of products.

8.1. Non linear mathematical model

We express our problem as an optimization problem and write a mathematical model to solve it. Then, we compare the result of this model and the Bayesian approach with different kernels. Mathematical model considers mean of random variables as satisfaction scores of product attributes. Decision variables are scalar instead of random variables. It aims at minimizing MSE expressed in Eq. (14).Minimize

$$MSE = \frac{\sum_{i=1}^{m}(z_i - \widehat{z}_i)^2}{m} \tag{16}$$

Subject to:

$$\sum_{j=1}^{k} w_j{}^*\overline{Y}_{ij} = \widehat{z}_i, \quad \forall i \tag{17}$$

$$\sum_{j=1}^{k} w_j = 1 \tag{18}$$

$$w_j \in (0, 1] \tag{19}$$

In objective function, $\widehat{z}_i$ is predicted overall satisfaction score of product and z_i is actual overall satisfaction score. The predicted overall score $\widehat{z}_i$ is computed with constraint (17), where $\overline{Y}_{ij}$ denotes mean of random variable Y_{ij}, satisfaction score of P_i with reference to A_j acquired by Eq. (8). Constraints (18) and (19) express decision variables of weight vector w.

According to fivefold cross validation conducted in MATLAB, average MSE of non-linear optimization method solved by interior-point-convex algorithm is obtained as 0.0483. Decision variable vector with lowest MSE is obtained as (4.94E-08 0.606 0.393 2.80E-08). Camera Resolution has the highest impact on overall score according to mathematical model. The ranking of weights is $w_2 \succ w_3 \succ w_1 \succ w_4$. The average MSEs of Bayesian method with different kernels are similar. The obtained scores are 0.0386, 0.0387, 0.0387 and 0.0388 with Uniform, Triweight, Epanechnikov quadratic and Gaussian kernels, respectively. The final ranking regarding impact of product attributes is $w_2 \succ w_4 \succ w_3 \succ w_1$.

Bayesian methodology is superior to optimization model in terms of computational efficiency as well. It takes about 41 s for 326,000 kernel function assessment in M-H sampling. However, it takes about 86 s to obtain feasible solution for optimization model with one objective function. Moreover, Bayesian methodology deals with performance scores represented as random variables. The weights are acquired as random variables. On the other hand, optimization model only considers expected values of performance scores regarding attributes. It does not give importance weights of attributes as random variable. M-H is a bootstrap sampling from the nonparametric kernel density model. A simulation can be conducted even though having incomplete dataset and the impact of product attributes are estimated as random variables according to simulation result. Therefore, we have realized more comprehensive analysis with Bayesian approach considering uncertainties.

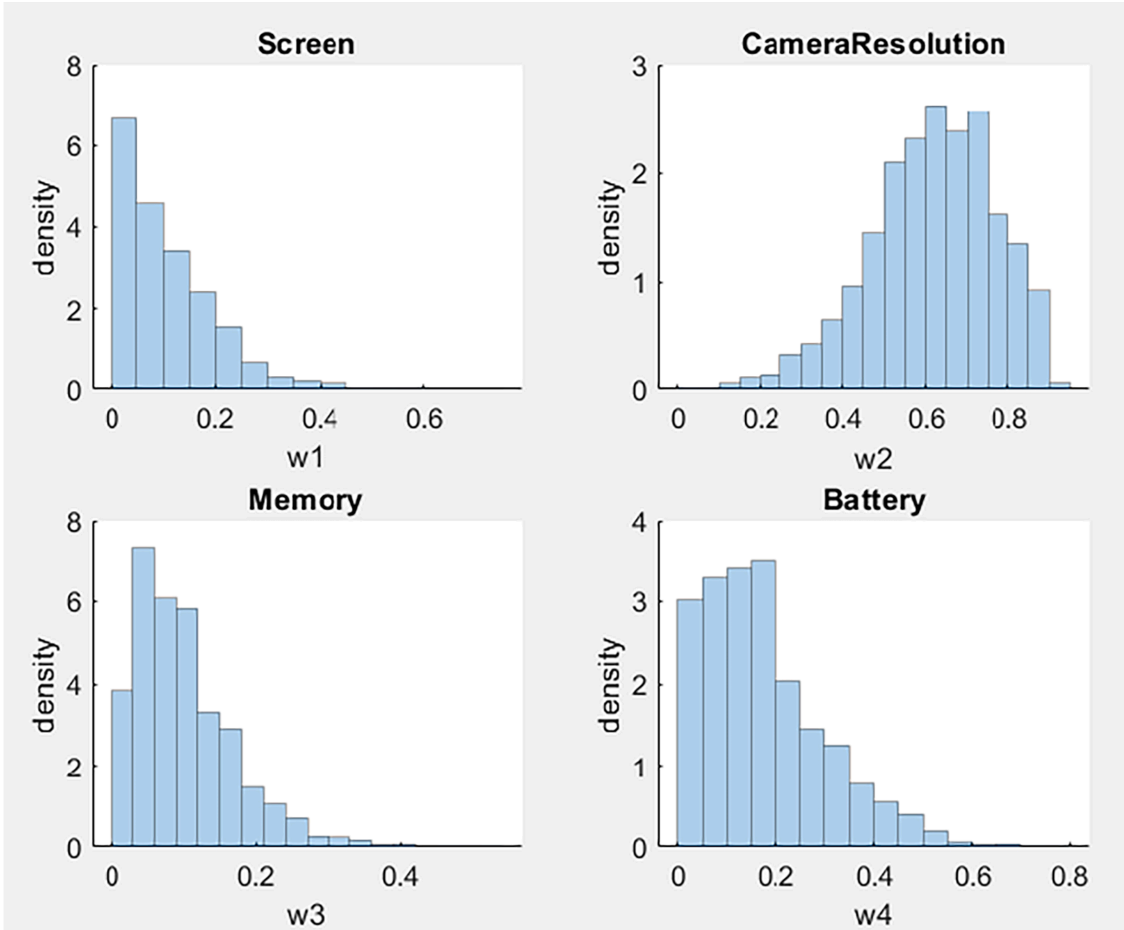

Fig. 6. Posterior probability distributions of weights with Triweight kernel: $\overline{w} = [0.139, 0.490, 0.159, 0.209]$.

8.2. Linear regression analysis with categorical predictors

The attributes Screen size (A_1), Camera Resolution (A_2), Memory (A_3), Battery (A_4) are considered as categorical predictors. Each attribute has seven categories as mentioned in section of Case Study. The first categories of categorical predictors (C11, C21, C31, and C41) are determined as reference levels in the model. Linear regression model of overall satisfaction scores is created as a function of attributes (Alsaffar, 2017). The formal model is given by Eq. (20).

$$Z = \beta_0 + \beta_1 * I_{(A_1=C12)} + \cdots + \beta_6 * I_{(A_1=C17)} + \cdots + \beta_{19} * I_{(A_4=C42)} + \cdots + \beta_{24} * I_{(A_4=C47)}. \quad (20)$$

where $I_{(A_i=C_{jk})}$ are indicator variables. For instance, the value of $I_{(A_1=C12)}$ is one if the value of Screen size (A_1) attribute is in category of C12. The overall satisfaction scores are indicated with vector of Z.

This regression model is created and solved in MATLAB. Table 6 displays regression coefficients (β), in other words, estimated contributions of attribute categories to overall satisfaction scores. The average MSEs of this regression model is 0.0581. Consequently, the proposed Bayesian method gives better result in cross validation comparison. It is important to highlight that regression analysis is not for weight determination. We have just found the impact of each attribute category to overall satisfaction score. The range of coefficients for each attribute is determined according to maximum and minimum values of coefficients. A high range value indicates that the related attribute has higher impact on change of the customer satisfaction score. Memory (A_3) has the highest impact on change of overall customer satisfaction scores.

8.3. Multilayer perceptron (MLP) neural network

MLP is one of the most widely utilized classes of neutral networks that can be effectively implemented to different complex problems (Shepherd, 2012; Baykasoglu & Baykasoglu, 2017; Kulluk, Ozbakir, & Baykasoglu, 2013). MLP is a supervised method which enables comparison of model-predicted results with known values of target variable. MLP includes three main parts: one input layer, one or more hidden layers and one output layer. The input layer contains the predictors, the hidden layers contain unobservable nodes, and output layer contain dependent variables. MLP uses back propagation learning algorithm for training process. In a MLP, an activation function is applied to each unit so as to deal with the potential nonlinearities between variables. Hyperbolic Tangent (Tanh) is one of the most well-known transfer functions. MLP is briefly introduced since it is out of scope of this research. More detailed information on MLP can be found in several studies (Shepherd, 2012; Xie, Zhang, & Lin, 2022).

MLP is implemented in IBM SPSS Neural Networks 28. Sum of squares error is utilized as the performance metric. Table 7 shows specifications of the best architecture of the MLP.

According to fivefold cross validation, the average MSEs of MLP model is calculated as 0.0421. In addition, IBM SPSS Neural Networks 28 allows to perform sensitivity analysis, which computes the importance of each predictor in determining the neural network using variance-based technique (Saltelli, Tarantola, Campolongo, & Ratto, 2004; IBM SPSS Neural Networks, 2022).

Predictors are ranked according to the sensitivity measure that is defined as follows:

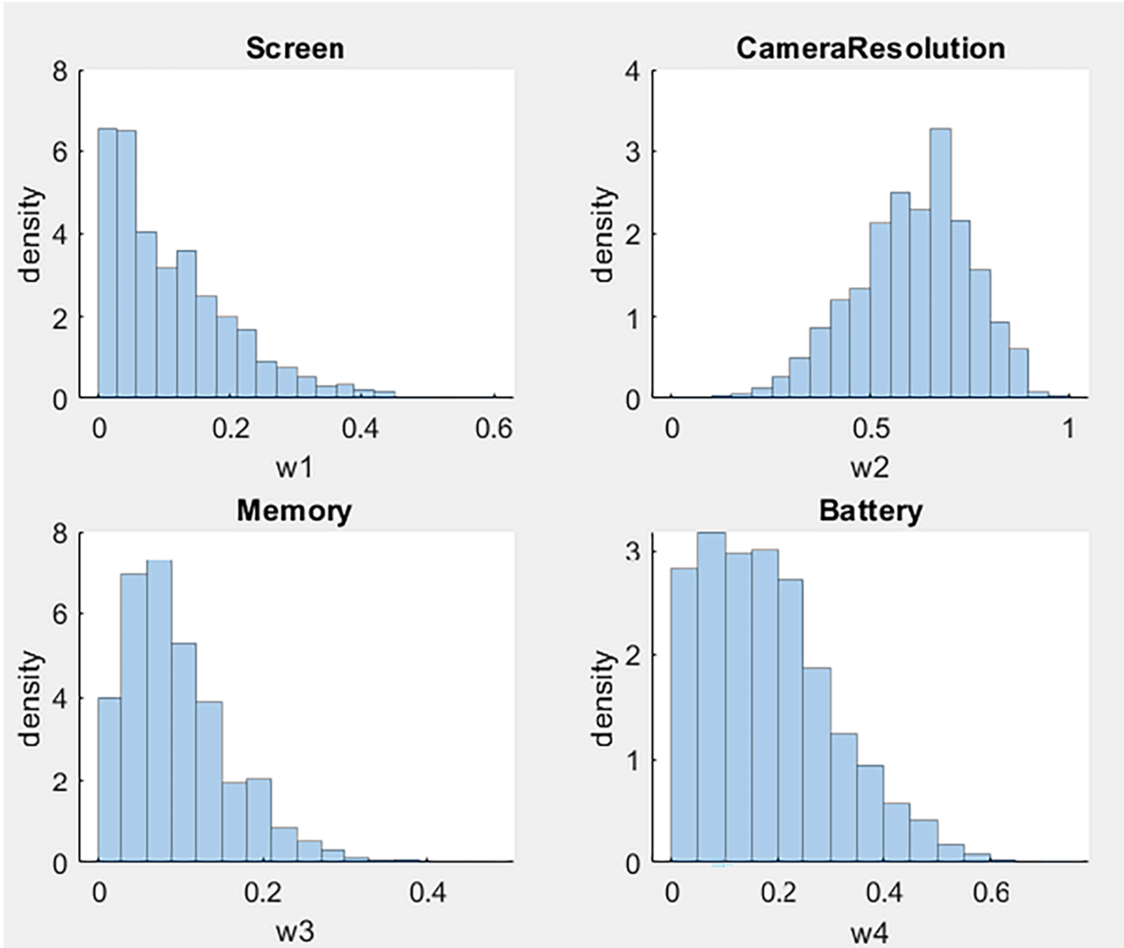

Fig. 7. Posterior probability distributions of weights with Epanechnikov kernel: $\overline{w} = [0.143, 0.492, 0.152, 0.211]$.

$$S_i = \frac{V_i}{V(Y)} = \frac{V(E(Y|X_i))}{V(Y)} \tag{21}$$

where V(Y) is the unconditional output variance. In the numerator, the expectation operator E calls for an integral over X_{-i} that is, over all factors but X_i, then the variance operator V implies a further integral over X_i. Predictor importance is then computed as the normalized sensitivity. The total sum of the overall variable importance of the ANNs is 1 (IBM SPSS Modeler 18.3 Algorithms Guide, 2022).

The importance values for attributes are 0.156, 0.322, 0.294, 0.229, respectively. Sensitivity analysis showed that Camera Resolution (A_2) is the most significant determinant of overall customer satisfaction scores.

In summary, Bayesian approach gives better performance metrics than other models. Table 8 presents the performance metrics and rankings regarding to the attributes. In addition, it is important to highlight the main purposes of OLS regression analysis and MLP are not weight determination. The obtained importance values give the relative contribution of each input variable to prediction. Moreover, Bayesian approach gives importance weights of attributes as random variable. The weights acquired by Bayesian approach have direct contribution in calculating overall performance scores.

9. Conclusions

This paper proposes a novel method for providing the impact of product attributes on customer satisfaction by analyzing online customer ratings. In the method, satisfaction scores of products with respect to attributes are represented by random variables whose values are extracted from overall scores such that the scores of products belonging to same category concerning an attribute are considered as observations of these random variables. The probability distribution functions of the random variables are calculated via kernel density estimation method. Overall scores are considered as values from mixture distributions made up of random variables pertaining to product attributes. Impacts of product attributes on overall scores are mixing proportions of random variables regarding product attributes, in other words, weight vector. We inference this weight vector by Bayesian inference algorithm, namely MCMC.

The proposed method is applied to analyses of online customer ratings on mobile phones. Based on our dataset, we acquire that camera resolution has highest impact on customer satisfaction. In addition, we conduct cross validation between Bayesian method, non-linear mathematical programming model, OLS regression model and MLP neutral network model. As a result, we get the better performance scores by employing the proposed Bayesian model. Moreover, different kernels are utilized in kernel density estimation such as Epanechnikov, Uniform, Triweight and Gaussian kernels. The results show that the kernel choice has not effect on rankings of weights. We obtain similar rankings and MSE scores with all of them. Section 9.1 summaries the major contributions of this study together with its practical implications.

9.1. Contributions and practical implications

Our study explores the weights of product attributes hidden in the customer satisfaction scores. This process is like deductive reasoning in reverse engineering, which gains knowledge from a finished product.

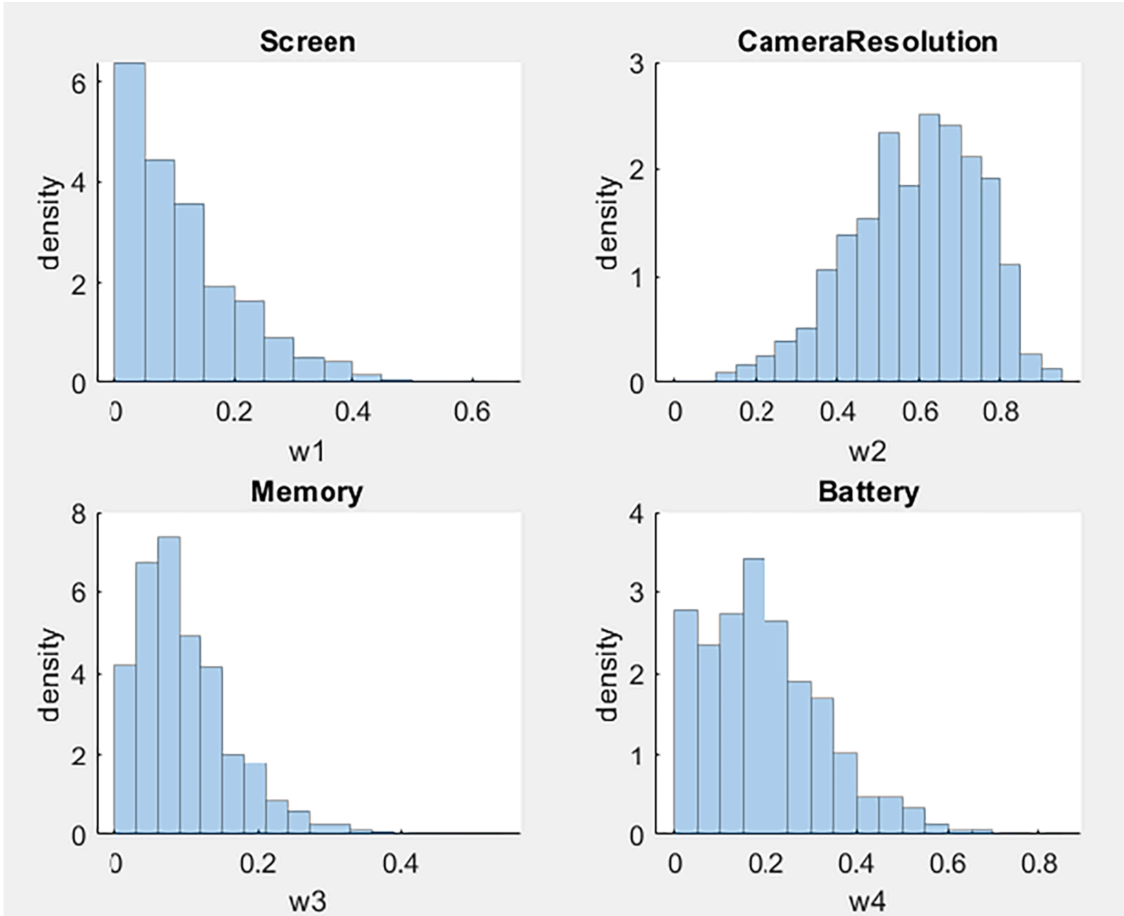

Fig. 8. Posterior probability distributions of weights with uniform kernel:$\overline{w} = [0.141, 0.468, 0.147, 0.242]$.

Table 5
Posterior probabilities for the order of attribute weights according to different kernels.

	Gaussian kernel	Triweight kernel	Epanechnikov Quadratic kernel	Uniform kernel
$P(w_2 \succ w_4)$	0.930	0.945	0.938	0.911
$P(w_3 \succ w_1)$	0.545	0.513	0.498	0.493
$P(w_2 \succ w_1)$	0.976	0.982	0.976	0.970
$P(w_2 \succ w_3)$	0.986	0.988	0.993	0.989
$P(w_4 \succ w_3)$	0.656	0.686	0.697	0.715
$P(w_4 \succ w_1)$	0.676	0.662	0.661	0.694
$P(w_2 \succ w_4 \succ w_3 \succ w_1)$	0.260	0.291	0.283	0.288
$P(w_4 \succ w_2 \succ w_3 \succ w_1)$	0.031	0.025	0.022	0.033
$P(w_2 \succ w_3 \succ w_4 \succ w_1)$	0.134	0.113	0.116	0.109
$P(w_2 \succ w_4 \succ w_1 \succ w_3)$	0.206	0.203	0.202	0.201

We have attempted to find out how the ratings of products are realized in minds of customers through an innovative analytical method based on Bayesian theory. This method uses the overall ratings such a finished object in reverse engineering, and attribute information of the rated products, and then extracts the weights of product attributes in the composition of the overall rating scores of these products. The overall rating scores, in other words, customer satisfaction scores are composed of the satisfaction level on each product attribute. What is the weight of each product attribute in this composition? This is the research question of the present study.

The weights, in other words, the output of the proposed method, can be used in several applications. Product ranking studies based on MCDM can use these weights as criterion weights. Therefore, this method can be

Table 6
Results of regression analysis.

Attributes	Categories	Coefficients	Std. Error	Range	Importance values
A1	C12	0.118	0.135	[−0.088 0.166]	0.184
	C13	0.166	0.170		
	C14	0.089	0.178		
	C15	0.116	0.192		
	C16	0.126	0.192		
	C17	−0.088	0.202		
A2	C22	0.383	0.179	[0 0.382]	0.277
	C23	0.270	0.157		
	C24	0.066	0.160		
	C25	0.345	0.162		
	C26	0.119	0.165		
	C27	0.231	0.171		
A3	C32	0.366	0.290	[0 0.519]	0.376
	C33	0.462	0.291		
	C34	0.511	0.300		
	C35	0.520	0.303		
	C36	0.436	0.320		
	C37	0.343	0.391		
A4	C42	−0.127	0.140	[−0.186 0.037]	0.162
	C43	−0.186	0.160		
	C44	−0.122	0.149		
	C45	−0.015	0.154		
	C46	−0.014	0.180		
	C47	0.038	0.180		
	(Intercept)	3.8	0.2142		

Table 7
MLP network information.

Input layer	Factors	Screen
		Camera
		Memory
		Battery
	Number of units[a]	28
Hidden Layer (s)	Number of Hidden Layers	1
	Number of Units in Hidden Layer 1[a]	1
	Activation Function	Hyperbolic tangent
Output Layer	Dependent Variables1	Overall satisfaction scores
	Number of Units	1
	Rescaling Method for Scale Dependents	Standardized
	Activation Function	Identity
	Error Function	Sum of squares

[a] Excluding the bias unit.

Table 8
Comparative study results.

	MSEs	RMSEs	MAPEs	Rankings
The proposed method with Gaussian Kernel	0.0386	0.1867	2.81	$w_2 \succ w_4 \succ w_3 \succ w_1$
The proposed method with Triweight Kernel	0.0387	0.1869	2.81	$w_2 \succ w_4 \succ w_3 \succ w_1$
The proposed method with Epanechnikov Kernel	0.0387	0.1871	2.81	$w_2 \succ w_4 \succ w_3 \succ w_1$
The proposed method with Uniform Kernel	0.0388	0.1873	2.81	$w_2 \succ w_4 \succ w_3 \succ w_1$
OLS Regression	0.0581	0.2349	3.85	$A_3 \succ A_2 \succ A_1 \succ A_4$
MLP Neutral Network	0.0421	0.1948	3.10	$A_2 \succ A_3 \succ A_4 \succ A_1$
Non-Linear Mathematical Model	0.0483	–	–	$w_2 \succ w_3 \succ w_1 \succ w_4$

regarded as a weighting method for MCDM analysis. It is worth mentioning that the proposed method is not only applicable to the case studies on customer satisfaction if it will be used in MCDM analysis. Although the analysis of online customer ratings is addressed in this article, it can also be applied to other decision-making problems, in which only data on overall satisfaction scores of alternatives are available. In other words, this study also proposes a new solution methodology in acquiring weights to criteria for MCDM analysis in an uncertain environment via Bayesian inference. To the best of our knowledge, it is the first study that extracts criterion weights by considering only overall performance scores of alternatives based on kernel density estimation and Metropolis-Hastings algorithm.

From the perspective of the case study, the present study fulfills the research gap in customer satisfaction literature by implementing the Bayesian solution in discovering the weights of product attributes on customer satisfaction scores expressed via online ratings. Product recommendation studies can make use of these weights to find appropriate products to be proposed to customers. The products with superior in the characteristic, to which our method assigns the highest weight, can be recommended on the web-sites. Adding such specialized product recommendation systems to the websites can increase the purchasing of the customers in these e-commerce websites. The proposed method has a clear logic and a simple computational process to support the companies in making decisions in product design and to gain insight into customer preferences for marketing. Advertising messages of the products can be defined according to these weights. Advertising companies might seek to call customer attention to the product by highlighting the superiority of the product attribute with the highest weight.

In terms of future research, the proposed method can be applied to online product ratings from other markets such as laptops, camera etc. The extended methodology might be developed based on online reviews as well as online ratings to obtain wider knowledge from customer opinions.

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CRediT authorship contribution statement

Sedef Çalı: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing. **Adil Baykasoğlu:** Conceptualization, Methodology, Writing – review & editing, Supervision.

Declaration of Competing Interest

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

Data availability

The authors do not have permission to share data.

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