

# Machine Learning-Driven Customer Segmentation: Exploring Customer Expectations of Personalization and Willingness to Pay

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**Introduction** | In the digital age, personalization has become essential to marketing and revenue management strategies, driven by the growing demand for tailored customer experiences. Consumer behaviour is shaped by a combination of internal factors (such as hedonic, cognitive, and uniqueness-seeking motivations) and external factors (including utilitarian and economic considerations). Traditional segmentation methods, relying mainly on static demographic data, often fail to capture the complexity and dynamism of contemporary consumer behaviour (Chandra et al., 2022; Seo & Buchanan-Oliver, 2019; Tyrväinen et al., 2020).

Unlike traditional profiling and segmentation, personalization focuses on individual customers rather than homogeneous groups, allowing for more nuanced and effective marketing strategies. As a result, personalization can significantly enhance customer segmentation approaches, ultimately leading to increased customer satisfaction and a higher willingness to pay (WTP) (Chandra et al., 2022; Currie et al., 2018; Tyrväinen et al., 2020). However, the current understanding of customers' expectations regarding personalization remains limited. This study aims to address this gap by employing the K-

means algorithm for customer segmentation. The objective of the study is to explore customer expectations regarding personalization and their WTP for personalized services. The study was conducted using a self-administered survey receiving 202 valid respondents, followed by *K*-means clustering, factor analysis, and ANOVA to segment customers based on behavioral, psychographic, and contextual data. The analysis explores six distinct clusters based on utilitarian, hedonic, cognitive, economic, uniqueness-seeking, and WTP factors.

**Theoretical background** | This research is grounded in configuration theory, which proposes that various combinations of factors – such as utilitarian, hedonic, cognitive, economic, and uniqueness-seeking – can lead to similar outcomes, including customer satisfaction or increased WTP (Cheng et al., 2022; Fiss, 2011). This means that the same conditions can result in different outcomes depending on their configuration. Customers express their preferences for products and services in ways that align with their expectations for personalization. Consequently, they invest more time gathering information and exploring alternatives when involvement is high and access to information is easy. Configuration theory helps explain this behaviour by highlighting how different combinations of factors shape decision-making outcomes. The perception of an object, scene, or phenomenon is not limited to the single elements that composite it, but it is a process that includes the entire perceptual experience. The importance of personalization grows as customers' needs and expectations for more targeted products and services increase, underscoring the necessity of understanding customer behaviour. Therefore, the integration of machine learning (ML) techniques (like *K*-means) in customer segmentation enables the identification of more dynamic and context-sensitive customer profiles, providing deeper insights into customer expectations regarding personalization (Deveau et al., 2023; Seo & Buchanan-Oliver, 2019).

**Methodology** | To cluster customers according to their personalization expectations a self-administered survey was conducted. The population for this research includes individuals who travelled in the last 12 months (before data collection) for leisure purposes and are UK residents. The study was conducted using various research and survey exchange groups using channels such as Facebook, LinkedIn, and Instagram between May and June 2022. The *K*-means clustering algorithm, an unsupervised ML technique, where the goal is to group a set of data points into *k* distinct clusters based on their similarities, was used to

explore customer segments based on a diverse dataset that included behavioural, psychographic, and contextual information (Fan et al., 2019). Explanatory factor analysis and principal component analysis were performed on 202 valid responses to determine the appropriate number of clusters. Subsequently, units were iteratively assigned into clusters until maximum between-cluster and minimum within-cluster distance were achieved. The correlation between clusters was tested using analysis of variances (ANOVA). Once identified, these clusters were characterized to analyse and understand customer behaviour.

**Findings** | The findings suggest that ML-driven segmentation techniques capture the diverse and evolving nature of customer preferences more effectively than traditional methods. Six distinct clusters of customers are identified based on their expectations of personalization and WTP. The study highlights that customers generally expect personalization but are not always willing to pay a premium for it. By leveraging ML, businesses can identify complex patterns in customer behaviour, enabling marketing efforts to be more closely aligned with individual expectations and can influence WTP (Pappas & Woodside, 2021). The cluster analysis further suggests that the relationship between the degree of personalization and customer WTP is not linear. WTP is somewhat influenced more by the customer's internal and external context than by their annual disposable income.

**Contributions and implications** | This research contributes to marketing and revenue management theory by demonstrating how integrating ML with configuration theory enhances customer segmentation. The findings offer valuable insights into various combinations of factors - including utilitarian and hedonic types of personalization, cognitive and economic benefits (customer philosophy), and the desire for uniqueness (novelty-familiarity continuum) - that shape customer expectations of personalization across different customer segments. Understanding the criteria for segmenting customers enables the selection of relevant and actionable variables. As customer behaviour and contexts evolve, regularly reviewing and refining segmentation strategies in response to market dynamics and competition is essential to maintain their relevance and effectiveness. The study also provides practical guidance for businesses, particularly in service industries like hospitality, on developing dynamic, personalized marketing and

pricing strategies that enhance both customer satisfaction and profitability (Buhalis et al., 2019).

**Conclusion** | Integrating ML into customer segmentation represents a significant advancement over traditional methods, providing a more nuanced approach to understanding and meeting customer expectations for personalization. It offers a more nuanced approach to understanding and fulfilling customer expectations of personalization. The findings suggest that, although customers expect personalization, they are not always willing to pay more for it. This study underscores the critical need for innovative segmentation strategies that address the complexities of contemporary consumer behaviour, thereby enabling more effective and personalized marketing outcomes (Cheng et al., 2022). To improve customer segmentation, marketing and revenue managers should gather relevant customer data from multiple sources, particularly first-party data collected directly from customers, and integrate this information to gain a comprehensive view of customer behaviour. Effective collaboration across marketing, sales, customer service, product development, and revenue management are crucial for understanding customer needs and executing segmentation strategies effectively.

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