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LATENT PROFILE ANALYSIS OF BEER CONSUMERS WITH THE APPLICATION OF R SOFTWARE

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Purpose: The goal of the paper is to analyze beer consumer preferences by applying latent profiles analysis.
Design/methodology/approach: Latent profile analysis (LPA) is used to identify the latent (unknown) profiles that are present. The main difference between latent profile analysis and well-known decompositional approach (e.g. conjoint analysis, discrete choice methods, etc.) is that LPA estimates the latent profiles, while in decompositional approach, profiles are prior known, and evaluated by customers.
Findings: The results identified two latent clusters, each with distinct preferences. Cluster 2 exhibited higher means for alcohol content, additional flavors, pasteurization, and filtration, whereas Cluster 1 showed stronger preferences for packaging, serving size, and beer color. The best model was determined based on the Bayesian Information Criterion (BIC), selecting the VVI model, where variances vary within and between classes, while covariances are set to zero.
Research limitations/implications: Latent profile analysis provides the information on latent profiles, but the determination of optimal number of profiles is challenging. We must rely in statistical criteria (e.g. AIC, BIC). Including too many latent profiles may lead to overfitting, capturing noise, rather than meaningful profiles. Also LPA assumes that, given the latent profile, observed variables are independent of each other. LCA is also sensitive to sample size. Many papers suggest to use at least 500 observations. Despite these limitations, LPA remains a valuable tool when applied carefully, with proper model validation and robustness checks.
Practical implications: The findings of this study provide valuable insights for breweries and marketers seeking to refine their product offerings and promotional strategies. By understanding the distinguishing characteristics of the identified clusters, businesses can develop targeted marketing campaigns and optimize their product portfolios to align with consumer preferences.
Originality/value: The paper uses a latent profile method that is not widely-known in Poland, and it is not a common method for preference analysis compared to decompositional approach (e.g. conjoint analysis, discrete choice methods, etc.).
Keywords: latent profile analysis, R software, preference analysis.
Category of the paper: research paper.

1. Introduction

Research on consumer behavior is conducted to improve the processes of adapting a company's offerings to buyers' expectations. In addition to known needs, potential needs must also be considered.

The study of consumer preference structures is based on the measurement and modeling of preferences (Bąk, 2000, pp. 71-72; Zwerina, 1997, p. 2). Preference measurement emphasizes the quantification of preferences. Thus, measurement allows preferences to be described numerically by constructing a measurement scale that enables a quantitative reflection of the relationships between evaluations of specific products (Bąk, 2000, pp. 71-72; Zwerina, 1997, p. 2). Preference modeling, on the other hand, is associated with explaining the process of consumer behavior, which results in the evaluation of offered products and, ultimately, the selection of one of them. These models serve as behavioral patterns for different consumer groups regarding the choice of specific products (Bazarnik et al., 1992, p. 85).

Preference measurement uses historical observations and anticipatory data describing consumer intentions. Consequently, we distinguish between revealed preference analysis methods and stated preference analysis methods (see Figure 1).

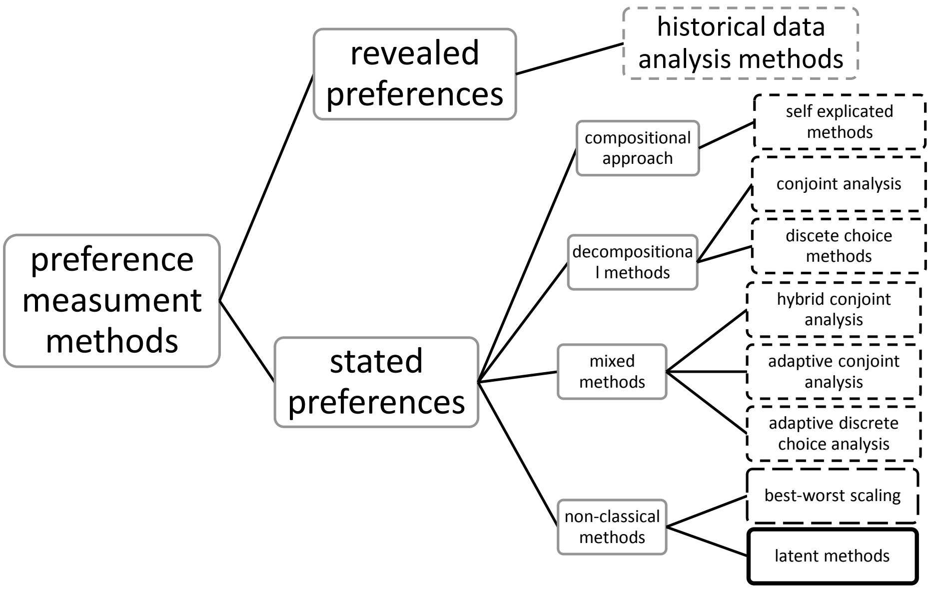

Figure 1. Types of preferences.

Source: Own elaboration based on Bąk, 2003, p. 212; Zwerina, 1997, pp. 2-3; Green, Srinivasan, 1990; Zwerina, 1997; Train, 2009; Aizaki, Fogarty, 2023.

Revealed preferences (RP) reflect actual market decisions made by consumers. The basis for analysis is statistical material collected through data registration on consumers' actual market choices. Other sources of such data include a posteriori interviews and surveys regarding consumers' past market choices. Thus, revealed preference research methods rely on historical data.

Stated preferences (SP), in contrast, pertain to consumers' hypothetical market behaviors. These research methods are mainly based on a priori data collected through surveys or interviews, which serve to register behaviors (intentions) expressed by consumers at the time of the survey or interview.

Consumer preference studies can be conducted using various methods. In the **compositional approach**, the idea of Fishbein’s attitude model is utilized, along with assumptions related to the expected value model, where the total utility of a multidimensional profile is a weighted sum of evaluations of variable levels, and the weights express the importance of individual variables (Walesiak, Bąk, 1997, p. 14; Zwerina, 1997, p. 3). Compositional models are a class of multivariable models, examples of which include regression models and discriminant analysis (Hair et al., 2019, pp. 562-563). Researchers using compositional models collect respondents’ ratings of various product or service attributes and then aggregate these ratings into overall preferences. In other words, analysts “compose” respondents’ preferences based on their evaluations of each attribute of a product or service.

In the **decompositional approach**, consumer preference analysis is conducted using conjoint analysis and choice-based methods (Bąk, 2000, p. 76). Decompositional models belong to a class of models that "decompose" consumers' total preferences. Using decompositional models, respondents are presented with a set of profiles, typically in the form of hypothetical or real products or services (Hair et al., 2019, p. 558). Statistical methods and computer algorithms are then used to decompose total preferences and estimate part-worth utilities (Bąk, 2004, p. 42).

In the **mixed approach**, models are formulated that combine features of both the compositional and decompositional approaches. This includes hybrid conjoint analysis models and adaptive conjoint analysis. Both methods employ two-phase preference measurement procedures (Bąk, 2004, p. 44). The first phase involves direct evaluations of attributes and their levels, while the second phase consists of assessing selected pairs or subsets of product or service profiles.

Discrete choice methods, unlike conjoint analysis, allow for the estimation of both part-worth and total utilities at an aggregated level across the entire studied group. Therefore, direct consumer segmentation cannot be conducted. To estimate utilities at the segment level within discrete choice methods, latent class models are used.

In recent years, numerous studies have been published on latent class analysis and finite mixture models. These models include one or more unobservable, latent variables that represent the characteristics of interest.

Due to different distributions of observable and latent variables, we can distinguish various latent variable models (Vermunt, Magidson, 2003, p. 1).

According to Bartholomew and Knot (Bartholomew, Knott, 2002, p. 3), four main types of models can be distinguished (see Table 1).

Table 1.
Classification of latent variable models

Observable Variable	Latent Variable	
	Continuous	**Categorical**
Continuous	Factor Analysis	Latent Profile Analysis
Categorical	Latent Trait Analysis	Latent Class Analysis

Source: Vermunt, Magidson (2003), p. 1.

There are three main areas of analysis using latent class models: segmentation, variable reduction, scale construction, and dependent variable prediction (Magidson, Vermunt, 2002, p. 2). Three primary types of latent class models can be distinguished (Magidson, Vermunt, 2002, p. 2):

a) Latent Class Cluster Models.
b) Latent Class Factor Models.
c) Latent Class Regression and Choice Models.

A latent class regression model, also known as a latent class segmentation model, is characterized as follows (Magidson, Vermunt, 2002, p. 5):

a) it is used to predict a dependent variable as a function of predictors,
b) it includes a latent variable with R categories, each representing a homogeneous population (class, segment),
c) a different regression model can be estimated for each latent segment,
d) it classifies characteristics into segments and simultaneously estimates regression models for each segment.

Advantages of this approach include (Magidson, Vermunt, 2002, pp. 5-6):

a) **Relaxing traditional assumptions:** Unlike conventional models where R = 1 is assumed, this approach allows separate regression models for each segment.
b) **Diagnostic statistics:** These allow for determining the optimal value of R.
c) **Model flexibility:** If R > 1, the model can be extended with additional explanatory variables to improve the accuracy of the analysis and segment assignment.

Latent class models account for consumer preference heterogeneity at the segment level (Zwerina, 1997, p. 75; Huber, Orme, Miller, 1999, p. 6). Studies using latent class models assume that the examined sample consists of a finite number of consumer groups with similar preferences, while significant differences exist between groups. These groups are not known a priori but are "latent" because neither the membership of individual consumers in specific segments nor the number of groups is known (Bąk, 2004, p. 134).

In multivariate statistics, latent class models belong to the group of mixed distribution models (Domański, Pruska, 2000, pp. 30-36). Mixture distributions are created by a defined number of component distributions, with each component's contribution determined by a mixing parameter. The sum of the mixing parameter values equals 1.

In segmentation studies using latent class models, the mixing parameter is interpreted as the segment size. The primary goal of model estimation is to determine the number and size of individual segments.

The procedure for constructing and estimating a latent class model is as follows (Bąk, 2004, pp. 134-135):

a) Defining the conditional distribution of a respondent's preferences (given the respondent's membership in a specific segment).
b) Determining the unconditional distribution of a respondent's preferences (a weighted sum of conditional distributions, where the weights are the estimated probabilities of segment membership).
c) Formulating the likelihood function (a product of individual preference distributions, assuming independence), with empirical preferences and unknown parameters as its arguments.
d) Estimating the model (estimating parameters and segment sizes).
e) Computing the a posteriori probabilities of respondents' segment membership.

The **Expectation-Maximization (E-M) algorithm** is more commonly used in software for estimating multivariate mixture distributions than other optimization algorithms (e.g., Newton-Raphson), due to its good convergence properties and ease of implementation (Wedel, Kamakura, 1998, p. 81).

The main advantage of the E-M algorithm is the **monotonic improvement** of the likelihood function value as the number of iterations increases. This procedure is also highly **versatile** and can be applied to various mixed distribution models. In decomposition methods, the E-M algorithm can be used for estimating **metric latent class models** (traditional conjoint analysis models, strong preference measurement scales) and **non-metric latent class models** (discrete choice models, weak preference measurement scales).

A crucial issue in estimating latent class models is **determining the optimal number of segments**.

The most commonly used selection criteria include (Kasprzyk, 2009, pp. 292-294; Shen, Sakata, Hashimoto, 2006, pp. 3-4):

a) AIC (Akaike, 1974),
b) AIC3 (Bozdogan, 1994, modification of AIC),
c) CAIC (Constant AIC, Bozdogan, 1992),
d) BIC (Bayesian Information Criterion, Schwarz, 1978),
e) ABIC (Sample-adjusted BIC, Scolve, 1987),
f) NEC (Normalized Entropy Criterion, Celeux and Soromrinho, 1996),
g) ICL BIC (Integrated Classification Likelihood BIC, Biernacki, Celeux, Govaert, 2000).

The model is selected based on the criterion yielding the **lowest value**.

2. Latent profile analysis

Latent profile analysis (LPA) is a latent variable modelling technique is also known as latent class cluster analysis (Vermunt, Magidson, 2002; Williams, Kibowski, 2016), finite mixture modeling (McLachlan, Peel, 2000). Several papers and books present an introduction to latent class analysis (LCA), latent profile analysis, and latent trait analysis (LTA) – e.g. Vermunt and Magidson (2002), Williams and Kibowski (2016), Muthén (2001), Muthén (2004), McLachlan and Peel (2000).

In latent profile analysis the goal is very similar to latent class analysis and in some context to cluster analysis in general. LPA aims to detect unknown (latent) clusters that might be there in the data set, and each of these clusters describes a latent profile (profile that is unknown before). The main difference between LPA and cluster analysis is that the LPA is a model-based approach, while cluster analysis in general is not.

LPA is a latent variable mixture model, where the term latent refers to a latent categorical variable that indicates cluster memberships for objects. This latent variable has K levels that relate to clusters (categories). The main assumption is that the observed sample is drawn from a heterogeneous population that is a mixture of K profile-specific distributions (6). LPA also assumes that the observed indicator variables are distributed normally within each latent profile (5). Besides that, LPA assumes local independence, which implies that the indicators are uncorrelated within the identified latent classes (7, 8).

When more than one continuous cluster indicator is used in the LPA, the multivariate representation of the model is (Pastor et. al. 2007):

$$f(\mathbf{y}_i|\boldsymbol{\theta}) = \sum_{k=1}^{K} \pi_k f_k(\mathbf{y}_i|\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k), \tag{1}$$

where:

$f(\mathbf{y}_i|\boldsymbol{\theta}) -$ is the distribution of cluster indicator $\mathbf{y}_i$, with given the model parameters $\boldsymbol{\theta} = (\pi_k, \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)$,

$\pi_k -$ non-negative weights that sum up to one,

$\boldsymbol{\mu}_k -$ mean vector,

$\boldsymbol{\Sigma}_k -$ covariance matrix.

Pastor et al. (2007) shows that while looking at the mean vector and covariance matrix we can have different LPA models:

a) The A model, where variances are estimated across profiles, and the covariances are constrained to be zero:

$$\begin{bmatrix} \sigma_1^2 & 0 & \cdots & 0 \\ 0 & \sigma_2^2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sigma_r^2 \end{bmatrix}. \tag{2}$$

b) In The B model, which allows for the variances to be freely estimated across profiles, the covariances are constrained to be zero:

$$\begin{bmatrix} \sigma_{1p}^2 & 0 & \cdots & 0 \\ 0 & \sigma_{2p}^2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sigma_{rp}^2 \end{bmatrix}.. \tag{3}$$

c) The C model where variances are still constrained to be the same across the profiles, the covariances are estimated, but like variances are also constrained to be the same across profiles:

$$\begin{bmatrix} \sigma_1^2 & \sigma_{12} & \cdots & \sigma_{1r} \\ \sigma_{21} & \sigma_2^2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{r1} & \sigma_{r2} & \cdots & \sigma_r^2 \end{bmatrix}. \tag{4}$$

d) The D model which specifies for the variances to be freely estimated across profiles and the covariances to be estimated equally across profiles:

$$\begin{bmatrix} \sigma_{1p}^2 & \sigma_{12} & \cdots & \sigma_{1r} \\ \sigma_{21} & \sigma_{2p}^2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{r1} & \sigma_{r2} & \cdots & \sigma_{rp}^2 \end{bmatrix}. \tag{5}$$

e) The E model that specifies variances to be equal across the profiles, but the covariances to be freely estimated across profiles:

$$\begin{bmatrix} \sigma_1^2 & \sigma_{12p} & \cdots & \sigma_{1rp} \\ \sigma_{21p} & \sigma_2^2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{r1p} & \sigma_{r2p} & \cdots & \sigma_r^2 \end{bmatrix}. \tag{6}$$

f) The F model where the variances and the covariances can be freely estimated across profiles:

$$\begin{bmatrix} \sigma_{1p}^2 & \sigma_{12p} & \cdots & \sigma_{1rp} \\ \sigma_{21p} & \sigma_{2p}^2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{r1p} & \sigma_{r2p} & \cdots & \sigma_{rp}^2 \end{bmatrix}. \tag{7}$$

These different specifications of covariance matrices can't be obtained from classical well-known cluster analysis. If we have the covariance matrix that is shown by eq. 3, then clustering techniques can be applied (Pastor et al., 2007, pp. 17-18). In latent profile analysis, the model parameters are being estimated with maximum likehood estimation via EM algorithm.

The logarithmic value of log-likehood is often used in latent modelling as it's mathematically tractable. The final log-likehood for a model and estimates of its parameters is used as a measure of model fit, where higher values indicating better fit.

In the case of maximum likelihood models, Akaike's information criterion (AIC) (Akaike, 1973) and Bayesian information criteria (BIC) (Schwartz, 1978) are usually used to select the best models.

3. Beer consumer analysis

The online questionnaire was designed to analyze beer consumer preferences, and the following attributes and levels were selected (see Table 2).

Table 2.
Attributes and their levels

Attribute	Levels
alcohol	no-alcohol
	low alcohol (2% to 4%)
	average (4% to 6%)
	strong (over 6%)
packaging	can
	bottle
	keg
Serving	0.33l
	0.4l
	0.5l
beer type	white
	light
	dark
taste	no additional taste added
	additional taste added (i.e. lemon)
pasteurization	pasteurized
	not pasteurized
filtration	filtered
	not filtered

Source: own elaboration.

As papers and simulations done by Spurk et al. (2020), Nylund et al. (2007), and Tein et al. (2013) suggest that a sample of around 500 respondents should be reasonable, based on past research and rules of thumb, our paper uses the sample of 510 respondents from Poland. The sample was collected via convenient sampling as well as snowball sampling. Although such a sample can't be used to test any statistical hypothesis, it can show general changes (Szreder, 2010).

510 respondents (convenience sample with snowball sample) evaluated each level for each attribute on a scale from 1 (not important) to 5 (very important). Although convenience sampling and snowball sampling do not allow the testing of statistical hypotheses about the whole population, they allow find of general changes and trends in the population.

General statistics for the whole sample are shown in table 3.

Table 3.
General statistics for the sample

Variable and levels		Sample
Gender	male	231
	female	279
Age	18-27	283
	28-35	68
	36-43	103
	44-60	47
	over 60	9
Education	primary	25
	lower secondary	17
	upper secondary	352
	higher	116
Domicile	village	176
	city up to 20k.	94
	city 20-100k.	103
	city 101-199k.	43
	city over 200k.	94

Source: own elaboration.

While convenience and snowball sampling provided practical means to recruit participants, these methods inherently limit the generalizability of our findings. Convenience sampling, by relying on readily available individuals, increases the likelihood of selection bias and may not fully capture the diversity of the broader population (Etikan et al., 2016).

Similarly, snowball sampling relies on social networks, which can lead to homogeneity in the sample, as participants may recruit others with similar characteristics or experiences (Noy, 2008). This can introduce bias and reduce the external validity of the study (Heckathorn, 2011).

Additionally, these non-random sampling techniques are susceptible to self-selection bias, as individuals who choose to participate may have specific motivations or perspectives that are not representative of the wider population (Palinkas et al., 2015).

Despite these limitations, steps were taken to mitigate bias by seeking diverse participant recruitment and clearly situating our findings within these methodological constraints.

To address these concerns, we have taken steps to encourage diverse recruitment and have acknowledged these limitations in our discussion. Future research employing probabilistic sampling methods, such as stratified or random sampling, may enhance the generalizability of findings (Bryman, 2015). Future research employing probabilistic sampling methods could further enhance the robustness and generalizability of results.

The average value for each attribute was calculated and all latent profile models were applied, estimated, and compared using the BIC criterion. Mclust package of the R software and mclust function were used for computation (Fraley et al., 2024).

The mclust function allows us to consider four model types:

1. EEI, where variances may vary within the class but not between classes. Covariances are fixed to 0 within and between classes.
2. EEE, where variances and covariances may vary within the class, but not between classes.

3. VVI – where variances may vary within and between classes, covariances are set to 0.
4. VVV, where both variances and covariances may vary within and between classes.

Results for different model types and 1 to 20 latent clusters are shown in Table 4.

Table 4.
Selection of the best model according to BIC

Number of clusters	model type			
	EEI	EEE	VVI	VVV
2	-2959,88	-3039,87	-2944,94	-3106,98
3	-2971,42	-3040,71	-2976,04	-3204,6
4	-2974,87	-3042,95	-3019,49	-3352,23
5	-2992,81	-3077,8	-3077,56	-3508,05
6	-3017,82	-3105,06	-3131,37	-3637,46
7	-3033,91	-3128,48	-3177,27	-3737,25
8	-3062,29	-3126,15	-3228,11	-3929,53
9	-3085,69	-3146,25	-3268,18	-3988,87
10	-3117,75	-3181,39	-3321,08	-4143,21
11	-3146,61	-3216,08	-3383,18	-4304,18
12	-3184,88	-3254,76	-3436,02	-4470,11
13	-3212,86	-3289,21	-3491,3	-4594,37
14	-3235,53	-3318,38	-3548,36	-4703,55
15	-3266,09	-3334,8	-3576,33	-4871,17
16	-3286,77	-3341,26	-3614,82	NA
17	-3326,77	-3396,73	-3666,24	NA
18	-3353,87	-3392,74	-3728,32	NA
19	-3385,74	-3416,78	-3784,07	NA
20	-3414,76	-3462,81	-3828,04	NA

Source: own computation with the application of the Mclust package for R software.

According to BIC the best one is the VVI model (BIC value is equal to −2944.937) where variances may vary within and between classes, covariances are set to zero for 2 latent clusters. Table 5 contains mean values for all variables and two latent clusters.

Table 5.
Profile means for all variables

Variable name	Cluster 1	Cluster 2
Alcohol	5.528	**6.090**
Packaging	**2.495**	2.395
Serving (volume)	**3.558**	3.065
Beer type	**1.500**	1.355
Add-ons	2.104	**2.164**
Pasteurization	0.488	**0.939**
Filtering	0.955	**1.201**

Source: own computation with the application of the Mclust package for R software.

Cluster 2 contains 121 respondents and has the highest means for alcohol, add-ons, pasteurization, and also filtering. Cluster 1 contains 129 respondents and has the highest values for packaging, volume, and color. If we would like to consider the three most important variables we can see (Table 4) that alcohol, volume, and packaging have the highest means for both clusters.

The class allocation in LPA is probabilistic in nature. Each subject in the data is assigned a probability for each of the estimated classes, based on their pattern of scores on the input variables. These probabilities can be inspected in the z-matrix (see Table 6 for uncertainty means).

Table 6.
Mean values for latent profiles

Group	Probability (profile 1)	Probability (profile 2)
1	0.841	0.159
2	0.078	0.922

Source: own computation with the application of the Mclust package for R software.

Probabilities are relatively high for group 2 and the first profile. In the case of group 2, these probabilities were relatively more stable in the case of profile 2.

4. Final remarks

This study applied Latent Profile Analysis (LPA) to segment beer consumers based on their preferences. Data was collected through an online questionnaire, analyzing attributes such as alcohol content, packaging, serving size, beer type, additional flavors, pasteurization, and filtration. A sample of 510 respondents from Poland was used, and various latent profile models were estimated using the Mclust package in R software.

The results identified two latent clusters, each with distinct preferences. Cluster 2 exhibited higher means for alcohol content, additional flavors, pasteurization, and filtration, whereas Cluster 1 showed stronger preferences for packaging, serving size, and beer color. The best model was determined based on the Bayesian Information Criterion (BIC), selecting the VVI model, where variances vary within and between classes, while covariances are set to zero.

Overall, the study provides valuable insights into beer consumer segmentation using LPA and demonstrates the effectiveness of R software in conducting such analyses. While the findings are insightful, the sampling method (convenience and snowball sampling) limits the generalizability of the results. Future research could involve a more representative sample and additional attributes to refine consumer segmentation further.

According to Statistics Poland (GUS) in 2020-2024 there were 340 breweries (large, small, craft, manufacturing). In Poland we can see that beer is gaining more and more popular. Breweries indicated that diversified hops is an essential element of beer production, as it allow to provide of different beer types. Also a rising popularity of non-alcoholic1 and low-alcohol beers2 (16% of beer market in Poland) and beers with add-ons is an interesting change in beer consumption (The Office of Competition and Consumer Protection, 2024, pp. 16-19). Besides

[1] They are called sometimes NoLo (no alcohol, low alcohol).

that small breweries (11% of the market) are becoming more popular as they offer more customer-oriented products. This is confirmed by our research where alcohol, serving (volume), and packaging are key factors for both profiles.

The findings of this study provide valuable insights for breweries and marketers seeking to refine their product offerings and promotional strategies. By understanding the distinguishing characteristics of the identified clusters, businesses can develop targeted marketing campaigns and optimize their product portfolios to align with consumer preferences.

Cluster 2, which exhibits the highest means for alcohol content, add-ons, pasteurization, and filtering, represents a consumer segment that values premium and craft beer attributes. This group is likely to be drawn to artisanal and high-quality beer offerings that emphasize unique ingredients and refined brewing processes. Marketing efforts targeting this cluster should highlight the craftsmanship, ingredient quality, and innovative brewing techniques employed in the production process. Additionally, emphasizing the purity and safety aspects associated with pasteurization and filtration can enhance brand appeal. Digital marketing strategies, including storytelling about the brewing process and collaborations with influencers in the craft beer industry, could further engage this audience.

Conversely, Cluster 1, characterized by the highest values for packaging, volume, and color, represents consumers who prioritize visual appeal and quantity. This group is likely to be more responsive to packaging innovations, larger serving sizes, and eye-catching designs. Breweries catering to this segment should invest in aesthetically appealing and sustainable packaging, as well as limited-edition designs to create a sense of exclusivity. Promotions that emphasize value, such as bulk purchasing incentives or variety packs, could enhance sales among these consumers. Retail placements in high-visibility areas and point-of-sale displays can also be effective in capturing their attention.

Furthermore, the three most important variables—alcohol content, volume, and packaging—demonstrate that both clusters share common factors influencing purchase decisions. This suggests that an integrated marketing approach could balance these elements to appeal to a broader audience. Breweries could segment their product lines, offering high-alcohol-content craft beers with premium packaging for Cluster 2, while simultaneously developing visually appealing, high-volume products for Cluster 1.

Lastly, probability analysis indicates relative stability in preferences for Cluster 2 across profiles, suggesting a strong brand loyalty or consistent demand pattern. Breweries can leverage this insight by fostering long-term relationships through loyalty programs, exclusive member offerings, and targeted communications that reinforce their commitment to quality and innovation. In contrast, the variability observed in Cluster 1 suggests a need for dynamic marketing strategies that capitalize on seasonal trends and promotional campaigns to maintain consumer interest. By integrating these insights into their marketing and product development strategies, breweries and marketers can enhance consumer engagement, drive sales, and build stronger brand loyalty within their respective target segments.

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