Wiadomości Statystyczne. The Polish Statistician, 2025, *70*(12), 35–54 https://doi.org/10.59139/ws.2025.12.2
Statystyka w praktyce / Statistics in practice
Zgłoszony/submitted: 29.09.2024, poprawiony/revised: 30.03.2025, zaakceptowany/accepted: 8.10.2025

The application of the best-worst scaling method to the identification of determinants of consumers' choices regarding a delivery method of products purchased online[1]

Marcin Pełka,[a] Aneta Rybicka[b]

Abstract. The measurement of preference and its analysis is a key concept in market research and more broadly, in the theory of economics. Preferences help explain how customers make their choices during purchases of goods and services on the market, e.g. which attributes of a product cause that consumers choose it. The theory of economics distinguishes between the stated and revealed customer preferences. The revealed customer preferences are consumers' actual market behaviours (purchased products), expressed by historic data. Stated preferences are customers' intentions to buy something. They can be measured in several ways, e.g. through conjoint analysis, discrete choice methods and best-worst scaling (BWS) – the latter in three variants, i.e. the objective, profile and multi-profile cases. When customers buy a product online, their choices are affected not only by products' attributes, but also by delivery options. As customers can select one of several available options of delivery, it is essential to identify and assess how these options impact their choices. Such information will make it possible to offer delivery options preferred by online shoppers.

The aim of the study presented in this paper is to identify, by means of a multi-profile BWS method, factors that affect customer choices regarding delivery methods while shopping online. The data for the study was collected from September 2023 to September 2024 via an online Google form, using convenient and snowball sampling methods. The analysis identifies the payment and delivery options as the key factors that affect the choice of a delivery method. The authors also demonstrate that BWS is a valuable tool in preference analysis in the delivery segment of the market and show the implications of their experiment as well as potential areas for future research.

Keywords: preference measurement, best-worst scaling, delivery method

JEL: C81, C87, D12, D81

[1] Artykuł został opracowany na podstawie referatu wygłoszonego na XXXII Konferencji Naukowej Sekcji Klasyfikacji i Analizy Danych Polskiego Towarzystwa Statystycznego, która odbyła się w dniach 19–20 września 2023 r. w Katowicach. / The article is based on a paper delivered at 32nd Scientific Conference of the Classification and Data Analysis Section of the Polish Statistical Association, held on 19–20 September 2023 in Katowice, Poland.

[a] Uniwersytet Ekonomiczny we Wrocławiu, Wydział Ekonomii i Finansów, Katedra Ekonometrii i Informatyki, Polska / Wroclaw University of Economics and Business, Faculty of Economics and Finance, Department of Econometrics and Computer Science, Poland. ORCID: https://orcid.org/0000-0002-2225-5229. Autor korespondencyjny / Corresponding author, e-mail: marcin.pelka@ue.wroc.pl.

[b] Uniwersytet Ekonomiczny we Wrocławiu, Wydział Ekonomii i Finansów, Katedra Ekonometrii i Informatyki, Polska / Wroclaw University of Economics and Business, Faculty of Economics and Finance, Department of Econometrics and Computer Science, Poland. ORCID: https://orcid.org/0000-0002-6453-9457. E-mail: aneta.rybicka@ue.wroc.pl.

Zastosowanie metody best-worst scaling do identyfikacji determinant wyborów konsumentów w zakresie dostawy towarów kupowanych online

Streszczenie. Pomiar i analiza preferencji są kluczowymi zagadnieniami badań marketingowych, a szerzej – teorii ekonomii. Preferencje pozwalają wyjaśniać, czym kierują się konsumenci, dokonując wyborów w trakcie zakupów towarów lub usług na rynku, np. jakie cechy produktu skłaniają konsumentów do jego wyboru. W teorii ekonomii wyróżnia się preferencje ujawnione, czyli rzeczywiste zachowania rynkowe konsumentów (dokonane zakupy – są to dane historyczne), i wyrażone, czyli intencje konsumenta (chęć zakupu). Preferencje wyrażone można mierzyć na wiele różnych sposobów, np. metodą analizy conjoint, metodami wyborów dyskretnych czy metodą best-worst scaling (BWS – skalowanie najlepszy-najgorszy), w trzech wariantach: obiektowym, profilowym i wieloprofilowym. W trakcie zakupów online na wybory konsumentów wypływają nie tylko atrybuty (cechy) produktów, lecz także opcje dostawy. Ponieważ konsument może wybierać spośród kilku opcji, istotnym zagadnieniem jest ich identyfikacja i ocena ich wypływu na dokonywane wybory. Informacje te pozwalają na oferowanie preferowanych opcji dostaw towarów kupowanych online.

Celem badania omawianego w artykule jest zidentyfikowanie, za pomocą wieloprofilowej metody BWS, czynników wpływających na wybory konsumentów w zakresie dostaw towarów kupowanych online. Dane do badania zbierano w okresie od sierpnia 2023 r. do sierpnia 2024 r. Wykorzystano formularz Google; zastosowano dobór według wygody i metodę kuli śnieżnej. Z przeprowadzonej analizy wynika, że głównymi determinantami wyboru w zakresie dostawy są sposoby płatności i sposoby dostawy. Autorzy pokazują także, że metoda BWS jest wartościowym narzędziem do oceny preferencji w segmencie dostaw, oraz wskazują następstwa eksperymentu i możliwe obszary dalszych badań.

Słowa kluczowe: pomiar preferencji, best-worst scaling, sposób dostawy

1. Introduction

Utility is the key concept in preference analysis. It can be seen as customer satisfaction from the selected products or services, i.e. the choices made. Direct measurement of utility is impossible, but the theory of economy allows its substitution with the concept of customer preference. This, in turn, makes it possible to evaluate utility, at least partially.

Customer preferences refer to the situation where an individual can evaluate various goods and services available on the market and choose from them. If products or services of the same type (class) are evaluated, it is possible to quantify the relation between them. In economics, such relations are referred to as preferences, because they provide information on customer attitudes towards products or services. Knowing preferences makes it possible to rank these products or services from the least to the most preferred one on an ordinal scale of measurement. This can be also done using a quantitative evaluation of each product by means of an interval or ratio scale of measurement.

The rise of e-commerce has significantly impacted consumer behaviour, particularly in terms of delivery preferences. Customers now consider various factors when choosing a delivery method, including the cost, speed, convenience, flexibility and environmental issues.

The analysis of customer choices regarding the method of delivery is a popular topic in the literature. Radyi et al. (2024) assert that the speed of delivery is a crucial factor in consumer satisfaction. They show that consumers prefer fast delivery, but only when it is reasonably priced. Kumar et al. (2025) came to a similar conclusion. Also Chodak (2024, pp. 35–62) emphasises the importance of the delivery method for consumers' satisfaction, and shows how AI-driven logistics improve the efficiency of deliveries and reduce their time. Kunharyanto et al. (2025) underscore the growing role of delivery options (especially self-service parcel lockers and scheduled deliveries) in consumer decisions. Similar conclusions were reached by Basch et al. (2025).

Kumar et al. (2024) demonstrate that consumers are becoming more conscious of eco-friendly shipping options. Wahyudien et al. (2024) find that other customers' reviews is an important factor in the choice of a delivery method. According to Bakar et al. (2025), consumers who use digital wallets or delayed-payment options tend to choose premium delivery services.

Finn and Louviere (1992) show the findings of a low-cost study designed to identify what citizens want a government department to do in response to polling that suggests high levels of concern about food safety. In the conclusion they recommend to apply best-worst scaling or other preference measurement methods to identify what actions are considered by citizens to be most effective in the context of food safety.

Pascoe et al. (2017) tasked their respondents with choosing the best and the worst from 16 statements relating to the attributes of a brand that represented the website communicativeness and aesthetics of the brand's website. As a result, the authors acquired a better understanding of consumer segmentation between bricks-and-mortar and online shops. Their findings indicated that a bifurcated audience, with one half focused on the communicativeness and the other on the aesthetics, is the most important in the online environment.

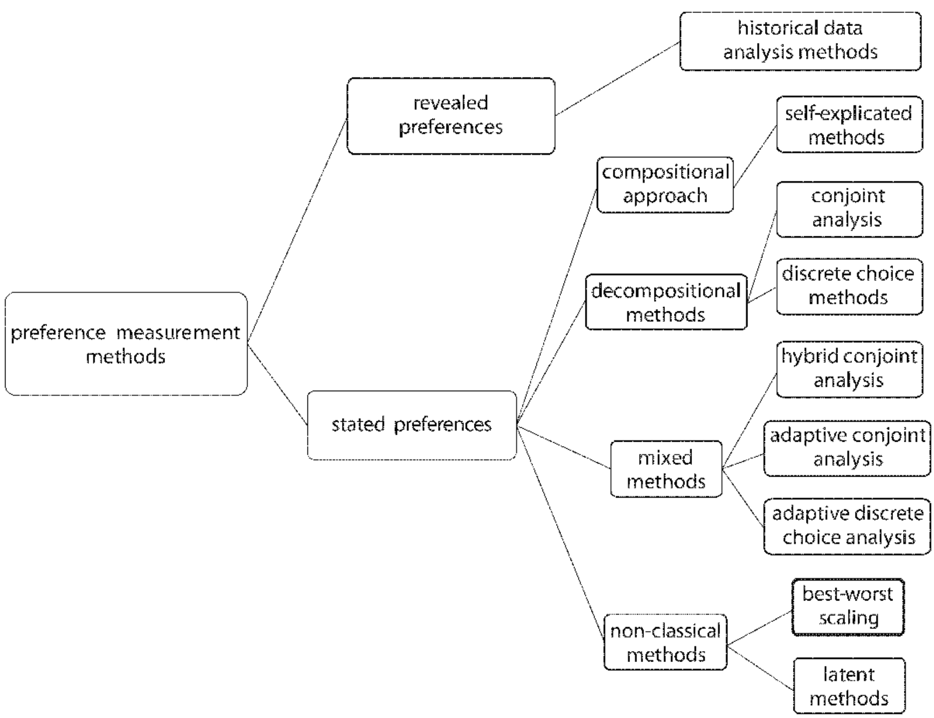
Rausch et al. (2021) found that conventional attributes of clothes such as fit and comfort, price-performance ratio and quality are of higher relevance to consumers than sustainable attributes. The most important sustainable attributes of clothes are the garment's durability, fair wages and work conditions for those who produce it, and an environmentally-friendly production process. However, respondents indicated that they preferred the latter three attributes over a 20% discount.

Focusing on the Polish market, Działo (2024) showed the importance of the option of delivery to parcel lockers. His study demonstrates that Polish customers have a growing preference for self-service pick-up points over home delivery, citing flexibility, prices and security as key reasons.

Hadaś et al. (2024) investigated the role of packaging and sustainable delivery in omnichannel retail. They show that 77% of young Polish customers (aged 18–25) like to have at least three delivery alternatives. Also, green delivery options, such as CO_2-neutral shipping, are gaining increasing popularity among younger people. By the same token, Witkowski et al. (2024) indicate that parcel lockers, fast delivery, and cost-effective shipping are customers' most pronounced preferences.

In general, customers' preferences can be divided into revealed preferences (actual purchases, reflected in historical data) and stated preferences (intentions). Each of them can be analysed by a specified method (see Figure 1).

Figure 1. Methods of customer preference measurement applied in marketing research



Source: authors' work based on: Aizaki and Fogarty (2023), Auger et al. (2007), Brand and Koplin (2023), Cohen (2009), Green and Srinivasan (1990), Train (2009) and Zwerina (1997).

Conjoint analysis methods and discrete choice methods (Figure 1) are related to some other decompositional approaches, such as adaptive conjoint analysis (ACA; for example Green et al., 1991; Rybicka, 2013), adaptive choice-based conjoint analysis (Bauer et al., 2015; Rybicka, 2013) and menu choice-based analysis (Pfaff, 2021; Rybicka, 2013). The paper by Rybicka (2013) presents a history of conjoint analysis and related methods. All of them have been developed from the well-known concept of conjoint measurement.

The analysis of consumer preferences involves the construction of models that reflect actual behaviour on the market and methods that allow these preferences to be measured (Zwerina, 1997). Consumer preference modelling should explain consumers' behaviour, including the process of product evaluation and the final choice of a product or service. So, consumer preference analysis uses track records and projections that describe consumers' intentions to buy a product or service (stated preferences) and decisions that have been made (final purchases, revealed preferences; see Figure 1).

Preference measurement by means of the best-worst scaling (BWS) uses the idea that the consumer can select the best and the worst option (alternative) on the market. To evaluate consumer preferences, BWS uses the counting and the modelling approaches, and in the case of the modelling approach, the well-known conditional logit model is applied (see McFadden, 1974 for details of this model).

As there are no papers dealing with the selection of a product delivery method and preference evaluation for the Polish market, this study aims to identify, by means of a multi-profile BWS method, factors that affect customer choices regarding delivery methods while shopping online.

2. Best-worst scaling methodology

The BWS methodology is based on the idea that a particular person faces choices of attributes, levels or profiles of three or more options. Each person can identify the best and the worst option (choice) in each collection (Louviere et al., 2015, p. 6). There are three types of BWS methods, namely the object case, also known as case 1 or maximum difference scaling (MaxDiff), the profile case, also known as case 2, and the multi-profile case, also known as case 3 (see Akizaki & Fogarty, 2019, 2023; Louviere et al., 2013, 2015).

The object case of BWS focuses on the attributes of a product or service; for example, in the case of a product, it focuses on the package size, price, country of origin, and quantity in a single package. The example of such a question is shown in Table 1.

Table 1. Example of an object case in BWS question

Attribute	Most important (best choice)	Least important (worst choice)
Package size	.	.
Price	x	.
Country of origin	.	.
Quantity in a package	.	x

Note. 'x' reflects choices made by a respondent, and '.' means that this element was not selected either as the best or the worst choice.
Source: authors' work based on Aizaki and Fogarty (2023).

The object case usually uses balanced incomplete block designs (Auger et al., 2007). These constitute a design category where a subset of profiles (treatments) is assigned to each block. The features in this design are expressed by the number of treatments (items, profiles), the size of a block (number of items, profiles per question), the number of blocks in the questionnaire and the number of replications of each item, as well as the frequency with which each pair of the items appears in the same block. Details on creating a balanced incomplete block design and estimations for object case of BWS can be found in Aizaki and Fogarty (2023) and Louviere et al. (2013, 2015).

In the profile case of BWS (also known as case 2 of BWS), each question has a profile that has three or more attributes and each of these attributes has two or more levels. Each profile is shown as a combination of the attributes and levels. Respondents then evaluate numerous profiles that were constructed using an experimental design. If we consider the same attributes as in Table 1, namely the package size, price, country of origin and quantity in a single package, then the following question could be shown to respondents (Table 2).

Table 2. Example of a profile case in BWS question

Attribute	Product	Most important (best choice)	Least important (worst choice)
Package size	small	.	.
Price	7 euro	x	.
Country of origin	Poland	.	x
Quantity in a package	10 pcs.	.	.

Note. As in Table 1.
Source: authors' work based on Aizaki and Fogarty (2019).

The multi-profile case of BWS is similar to discrete choice methods. A BWS question consists of three or more profiles. Each of them has two or more attributes, each with two or more levels. In contrast to discrete choice methods, where respondents select one of the profiles, in BWS respondents are asked to choose the best and the worst profile. This evaluation is made until all profiles have been evaluated. The example of a multi-profile case of BWS is shown in Table 3.

Table 3. Example of a multi-profile case in BWS question

Attribute	Product 1	Product 2	Product 3
Package size	small	average	large
Price	7 euro	10 euro	30 euro
Country of origin	Poland	Germany	Slovakia
Quantity in a package	10 pcs.	20 pcs.	40 pcs.
Most important (best choice)	.	x	.
Least important (worst choice)	.	.	x

Note. As in Table 1.
Source: authors' work based on Louviere et al. (2015).

Many different approaches can be used to obtain choice sets for multi-profile BWS cases. Usually, a basic design with fractional factorial design and balanced incomplete block designs are used. In this paper, the balanced incomplete block design is used where a fractional factorial design was applied at the start.

There are two ways to analyse the responses of the multi-profile case of BWS: the counting and modelling approaches.

The counting approach calculates several types of scores based on the number of times (usually frequency or count) item i was selected as the best B_{in} or the worst W_{in} item among all the questions for the n-th respondent. We can distinguish between (disaggregated) individual-level scores and (aggregated) total-level scores (Aizaki & Fogarty, 2023; Cohen, 2009).

The first category is an individual-level (disaggregated) analysis of BW and the standardised BW (Aizaki & Fogarty, 2023, p. 3):

$$BW_{in} = B_{in} - W_{in}, \tag{1}$$

$$\text{std.}\,BW_{in} = \frac{BW_{in}}{r}, \tag{2}$$

where:
BW_{in} is the best-worst score for the i-th item for the n-th customer,
B_{in} is the number of times the i-th item was selected as the best one,
W_{in} is the number of times this item was selected as the worst one,
r is the frequency with which item i appears across all the questions.

Aggregated versions of these scores can be obtained by adding individual-level scores from all respondents. The frequency with which the i-th item is selected as the best among all N respondents is defined as $B_i = \sum_{n=1}^{N} B_{in}$. The frequency with which the i-th item is selected as the worst among all N respondents is defined as $W_i = \sum_{n=1}^{N} W_{in}$. The aggregated scores are defined as follows (Aizaki & Fogarty, 2023, p. 3):

$$BW_i = B_i - W_i, \tag{3}$$

$$\text{std.}\, BW_i = \frac{BW_i}{Nr}, \tag{4}$$

$$\text{sqrt.}\, BW_i = \sqrt{B_i / W_i}, \tag{5}$$

$$\text{std. sqrt.}\, BW_i = \frac{\text{sqrt.}\, BW_i}{\max \text{sqrt.}\, BW_i}. \tag{6}$$

The modelling approach uses the same idea as discrete choice models to analyse consumer responses (Train, 2009). There are three types of best-worst models that differ in relation to how the customer indicates the best and the worst items in each choice set (profile set). The customer choices can be modelled as follows (Aizaki & Fogarty, 2023, p. 4):

1. The MaxDiff model assumes that customers select a pair of items (profiles) i and j from a choice set C, where the i-th item is selected as the best and the j-th item as the worst, and the difference in utility between these two items is the biggest one among all possible utility differences. The probability of selecting item i as the best and j as the worst can be modelled by using the conditional logit model:

$$P_n(i,j) = \frac{\exp\left(v_i - v_j\right)}{\sum_k \sum_{l,k \neq l} \exp(v_k - v_l)}. \tag{7}$$

2. The marginal model assumes that consumers select items i and j from a choice set as the best and the worst one when the utility of item i is the maximum and the utility of j-th item is the minimum. Using the conditional logit model, the probability of selecting item i as the best and j as the worst can be expressed in the following way:

$$P_n(i,j) = \left[\frac{\exp(v_i)}{\sum_k \exp(v_k)}\right]\left[\frac{\exp(-v_j)}{\sum_k \exp(-v_k)}\right]. \tag{8}$$

3. The marginal sequential model assumes that consumers select the i-th item as the best one in a choice set and then the j-th item as the worst one among the remaining items in the choice set when the i-th item is excluded. The probability of selecting item i as the best and j as the worst can be expressed as:

$$P_n(i,j) = \left[\frac{\exp(v_i)}{\sum_k \exp(v_k)}\right]\left[\frac{\exp(-v_j)}{\sum_{l\subset\{C-i\}} \exp(-v_l)}\right], \tag{9}$$

where: C is the choice set, and i is the i-th item.

In Equations 7, 8 and 9, v_i is the systematic component of the utility of the i-th item, which is assumed to be given by (Aizaki & Fogarty, 2023, p. 4):

$$v_i = b_i D_i, \tag{10}$$

where:

b_i is a coefficient to be estimated,

D_i is a dummy variable with the value of 1 if the i-th item is included in the choice set and 0 if it is not included.

If we want to include and consider the effects of other covariates on the coefficients for item dummy variables, the systematic component of the utility of the i-th item can be expressed in the following way (Aizaki & Fogarty, 2023, p. 4):

$$v_i = \left(b_{0i} + \sum_{q=1}^{Q} b_{qi} X_q\right) D_i, \tag{11}$$

where:

X_q are the covariates, and the various coefficients are estimated,

$q = 1, \ldots, Q$ is the number of coefficients,

b_{qi} is the coefficient for the q-th variable and the i-th item.

Equations 7, 8 and 9 are derived on the basis of the conditional logit model. However, other discrete choice models, such as mixed logit models or latent class models, can also be applied in this case (Lusk & Briggeman, 2009; Yang et al., 2021).

Estimated covariates for dummy variables (Equation 10) can be used to obtain preference shares as follows (Cohen, 2009; Lusk & Briggeman, 2009):

$$S_i = \frac{\exp(\hat{b}_i)}{\sum_k \exp(\hat{b}_k)}, \tag{12}$$

where:

S_i is the share for the i-th item,

$\hat{b}_i$ is the estimated coefficient corresponding to the i-th item.

In the empirical example, a balanced incomplete block design will be used and the MaxDiff model will be applied. A balanced incomplete block design creates profiles from a fractional factorial design and then assigns the profiles into choice sets via a balanced incomplete block design (Raghavarao & Padgett, 2005). In the balanced incomplete block design, items within the experiment are balanced, orthogonal and adequately randomised under the assumption of the random utility theory (Green, 1974). The major benefit of using the balanced incomplete block design is its capability of greatly decreasing the number of choice sets to be evaluated while maintaining the balanced appearance and co-appearance of items across sets (Green, 1974; Raghavarao & Padgett, 2005).

If we assume that we have a set of k items, a balanced incomplete block design will generate s choice sets. Each choice will have m items. To minimise the difficulty, m should always be smaller than k. Each item then appears r times and each pair of items appears λ times. This balanced incomplete block design (experiment) must satisfy an integer's λ values, and $r(m-1)/(k-1)$ will be used to calculate the lambda value (Massey et al., 2015). If s is equal to k, the design is known as symmetrical (Raghavarao & Padgett, 2005). Although a symmetrical design is best, it is not always arithmetically possible. But there should be a positional balance in an ideal design that controls possible order effects with each respondent seeing each item in the first, second, etc. position across the sets (Lee et al., 2007). If the experiment is not symmetrical, it is required that the order of items visible in each choice set is randomised to control for possible order effects (Massey et al., 2015).

3. Customer delivery choices in online purchases

The choice of a delivery method is an important task in an online purchase (for example Bauerová, 2018; Dias et al., 2021; Koyuncu & Bhattacharya, 2004; Luttermann et al., 2021; Nguyen et al., 2019; Rotem-Mindali & Salomon, 2007).

Most of the above papers focus on the following attributes of a delivery: its speed, time slots, daytime/evening delivery, delivery date and delivery fee (Bauerová, 2018; Dias et al., 2021; Koyuncu & Bhattacharya, 2004; Luttermann et al., 2021; Nguyen et al., 2019).

Rotem-Mindali and Salomon (2007) focus on decision-making processes while buying, especially in e-commerce, whereas delivery is analysed only as a factor that can be selected before, during or after the purchase. Bauerová (2018) expands the group of external factors in the online customer decision-making process and examines the influence of the offered services and delivery conditions on consumers' decision-making in online grocery shopping. The results of her study show that customers are mostly concerned with the delivery time and charge (price). Nguyen et al. (2019) come up with a similar conclusion, namely that the delivery fee is the most important factor concerning online purchases, followed by non-price delivery attributes. The study by Dias et al. (2021) shows that the price of deliveries (shipping) affects customers according to their gender. Their perception of delivery options also depends on their age, income, frequency of shopping online, prices and degree of privacy.

Luttermann et al. (2021) analysed online grocery sales using discrete choice methods. Their results show that the delivery method (type of a delivery vehicle), place of the delivery, packaging and delivery time are crucial during purchases.

Koyuncu and Bhattacharya (2004) assessed the influence of the potential benefits and risks on online shopping. They examined factors such as the speed of delivery, its cost, payment risks and delivery issues. The authors demonstrated that longer delivery time might discourage customers from shopping online.

4. Results and discussion

This paper uses 143 responses out of the total 161 collected from customers from Dolnośląskie Voivodship (convenience and snowball sampling techniques; as a result, the dataset is not a random sample). The data was gathered via a Google form which contained profiles in 12 blocks with 6 options (profiles) in each of them, and the possibility of abstaining from selecting any option was excluded.

Each profile was described by four attributes, and each of them had three levels[2]:

- delivery time (up to 3 days, 4–7 days, 8 days or longer),
- place of delivery (parcel locker, delivery person, access point or store),
- shopping venue (physical store with an online website, online store, shopping platform),
- payment (payment gateway, mobile, cash, upon delivery).

An example of profiles in a block is presented in Table 4.

Table 4. Example of profiles in a single block with answers

Profile attribute	Profile 1	Profile 2	Profile 3	Profile 4	Profile 5	Profile 6
Delivery time	up to 3 days	4–7 days	4–7 days	8 days or longer	8 days or longer	8 days or longer
Place of delivery	access point or store	delivery person	access point or store	parcel locker	delivery person	access point or store
Shopping venue	on-line store	on-line store	physical store with website	on-line store	shopping platform	physical store with website

[2] This study does not contain information on concrete prices, as it is not focused on any specific brand or type of purchased products.

Table 4. Example of profiles in a single block with answers (cont.)

Profile attribute	Profile 1	Profile 2	Profile 3	Profile 4	Profile 5	Profile 6
Payment	cash or on delivery	payment gateway	mobile	mobile	cash or on delivery	payment gateway
Best choice	.	x	.	.	.	.
Worst choice	x	.	.	.	.	.

Note. As in Table 1.
Source: authors' work.

The authors checked the required sample (N) size by using the rule of thumb $N > \frac{500 \cdot L}{T \cdot J}$, where J is the number of alternatives per choice, L is the number of attribute levels, and T is the number of choice tasks per respondent. In the experiment we have $J = 6, L = 12, T = 12$, thus $N > \frac{(500 \cdot 12)}{(12 \cdot 6)} = 83.33 \approx 84$ objects. We have 143 objects, so the experiment meets the requirement of the minimum number of objects.

As we have 143 respondents, 12 blocks, and 6 profiles, we will present aggregated (unique profiles) statistics in Table 5.

Table 5. Basic statistics for profiles

Profile number	Delivery time	Place of delivery	Shopping venue	Payment	B_i (SD)	W_i (SD)	BW_i	std. BW_i	$\sqrt{BW_i}$	std. $\sqrt{BW_i}$
1	up to 3 days	access point	online	cash	416 (0.49)	440 (0.51)	–24	–0.03	0.97	0.36
2	up to 3 days	delivery person	platform	mobile	813 (0.88)	112 (0.12)	701	0.76	2.69	1.00
3	up to 3 days	parcel locker	physical	payment gateway	861 (0.87)	130 (0.13)	731	0.74	2.57	0.96
4	4–7 days	access point	physical	mobile	190 (0.23)	647 (0.77)	–457	–0.51	0.54	0.20
5	4–7 days	delivery person	online	payment gateway	254 (0.30)	604 (0.70)	–350	–0.41	0.65	0.24
6	4–7 days	parcel locker	platform	cash	345 (0.44)	452 (0.56)	–107	–0.13	0.87	0.32
7	8 days or longer	access point	platform	payment gateway	190 (0.23)	647 (0.77)	–457	–0.55	0.54	0.20
8	8 days or longer	delivery person	physical	cash	190 (0.22)	655 (0.78)	–465	–0.56	0.54	0.20
9	8 days or longer	parcel locker	online	mobile	190 (0.22)	667 (0.78)	–477	–0.57	0.53	0.20

Note. B_i is the number of times that the *i*-th profile was selected as the best one, W_i is the number of times that the *i*-th profile was selected as the worst one, BW_i as in Equation 3, standarised BW_i as in Equation 4, square root of BW_i as in Equation 5, std. sqrt. BW_i as in Equation 6.
Source: authors' work.

We can see that the delivery option within three days by a delivery person of a product purchased through an online platform with a mobile payment has the highest standardised square root of BW_i. The second-highest standardised square root of BW_i has been observed for the delivery within three days to a parcel locker, where the traditional shop was the transaction place, and the payment was done by payment gateway.

As mentioned before, the preferences were estimated using the conditional logit model (the `clogit` function from the `survival` R package – see Therneau et al., 2024) under the assumption that customers follow the MaxDiff model while making choices, and the same assumptions were used for the mixed logit model (the `logitr` function from the `logitr` R package; Helveston, 2024). The results of the estimation for the coefficients in the case of the conditional logit model are presented in Table 6. The odds ratio for all the levels of the conditional logit is shown in Figure 2. The results of the estimation for the coefficients in the case of the conditional logit model are presented in Table 7.

Table 6. Results of the estimation of the conditional logit model

Level	Coefficient	Exp (coefficient) odds ratio	Standard error (coefficient)	*z*	*p*-value
Delivery time					
8 days or longer	−1.05154	0.34940	0.11483	−9.157	< 2e−16
Up to 3 days	0.63972	1.89596	0.09542	6.704	2.02e−11
Place of delivery					
Access point	1.07788	2.93845	0.30565	3.527	0.000421
Delivery person	1.81206	6.12307	0.30135	6.013	1.82e−09
Parcel locker	1.59808	4.94354	0.30516	5.237	1.63e−07
Shopping venue					
Physical store	0.97134	2.64147	0.10772	9.017	< 2e−16
Shopping platform	0.11952	1.12696	0.10964	1.090	0.275654
Payment					
Mobile	1.12723	3.08710	0.11082	10.172	< 2e−16
Payment gateway	1.84005	6.29683	0.11336	16.232	< 2e−16

Source: authors' work using the `clogit` function of R software.

Additional summary statistics for the model are: Rho-squared at 0.2510276, adjusted Rho-squared at 0.247268, Akaike information criterion (AIC) at 3603.876, Bayesian information criterion (BIC) at 3649.581, log-likelihood at start at −2393.864 and log-likelihood at convergence at −1792.938.

Table 7. Results of the estimation for the mixed logit model

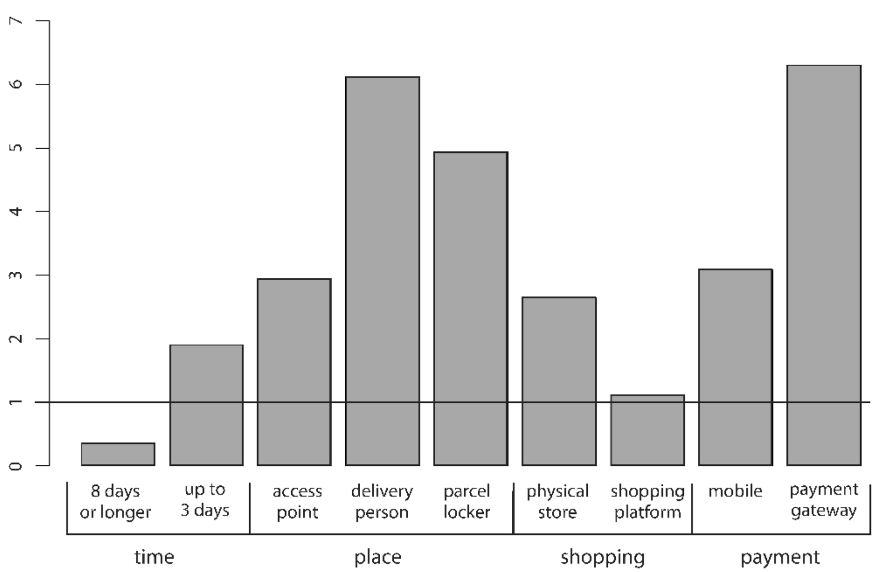
Attribute and level	Coefficient	Exp (coefficient) odds ratio	Standard error (coefficient)	*z*	*p*-value
Payment: payment gateway	1.52069	4.57538	0.12770	11.9080	< 2.2e–16
Place: delivery person	1.30585	3.69082	0.14921	8.7517	< 2.2e–16
Place: parcel locker	1.14210	3.13334	0.11558	9.8817	< 2.2e–16
Place: access point	1.08195	2.95043	0.13238	8.1731	< 2.2e–16
Payment: mobile	0.86682	2.37933	0.10140	8.5489	< 2.2e–16
Shopping: physical store	0.61249	1.84502	0.11035	5.5505	2.85e–08
Time: up to 3 days	0.46946	1.59913	0.11529	4.0721	4.66e–05
Shopping: shopping platform	0.40096	1.49326	0.11833	3.3885	0.000703
Time: 8 days or longer	–1,14838	0.31712	0.12212	–9,4035	< 2.2e–16

Note. All attributes and levels are sorted by a decreasing odds ratio.
Source: authors' work using the `logitr` function of R software.

Additional summary statistics for the model are: log-likehood at 1016.016, null log-likehood at 1630.28, Akaike information criterion (AIC) at 2048.03, Bayesian information criterion (BIC) at 2088.59, McFadden's R^2 at 0.3778, and adjusted McFadden's R^2 at 0.371878.

The results for the mixed logit model seem to be very similar to those obtained from the conditional logit model.

Figure 2. Odds ratio for attribute levels



Source: authors' work using R software.

As the raw coefficients of the conditional logit model are rather difficult to interpret and understand, we employed the odds ratio. It represents the relative possibility of an event's occurrence due to the presence of a factor that is described by an independent variable. An odds ratio > 1 implies that an event (a choice in the case of preferences) is more likely to happen, while an odds ratio < 1 implies that this event is less likely to happen. If the odds ratio = 1, the variable has no impact on the event. In each of these cases, we assume that other factors (variables) are constant, and all external factors that are not in the model are the same.

In our case, the factor (variable) that has the highest impact on the customer choices of delivery options while shopping online is the place of delivery, whereas the payment method, the shopping venue, and the time of delivery are the least important factors. If we look at odds ratios for the variable levels (Figure 2), we can observe the greatest odds ratio for the payment made via a payment gateway, and the second-greatest one for the delivery by a delivery person. Table 8 presents the impact of each variable level on customer choices.

Table 8. The impact of odds ratio and attributes on customer choices for both models

Attribute and level	Clogit odds ratio		Logitr odds ratio	
		rank		rank
Payment: payment gateway	6.29683	1	4.57538	1
Place: delivery person	6.12307	2	3.69082	2
Place: parcel locker	4.94354	3	3.13334	3
Payment: mobile	3.08710	4	2.37933	5
Place: access point	2.93845	5	2.95043	4
Shopping: physical store	2.64147	6	1.84502	6
Time: up to 3 days	1.89596	7	1.59913	7
Shopping: shopping platform	1.12696	8	1.49326	8
Time: 8 days or longer	0.34940	9	0.31712	9

Source: authors' work using R software.

Both the conditional logit and mixed logit models show that the payment via a gateway and the delivery method by a delivery person or to a parcel locker have the most significant impact on customer choices.

If we want to generalise these results, it can be said that payment methods and delivery options are the key factors for Polish customers. Similar results were achieved by Basch et al. (2025), Działo (2024), Kumar et al. (2025), Kunharyanto et al. (2025), Radyi et al. (2024) and Witkowski et al. (2024). This confirms that Polish customers' patterns of behaviour regarding the selection of a delivery option are more general. In BWS, respondents have to evaluate multiple profiles in a set or abstain from doing it (if there is such an option). The best and the worst profile always have to be indicated; if one is missing, the data is incomplete. Therefore, BWS is a more complex decision process than a discrete singular-choice task. BWS might also appear more laborious to respondents, might reduce saturation and lead to larger mistake rates, especially if we deal with large sets of profiles with many attributes and their numerous levels. Therefore, best-worst datasets must be estimated by means of proper techniques. As regards best-worst scaling, there is also a risk of the potential dominance of salient attributes. What is more, the choice of the best and the worst profile is not realistic – people choose one product or service (or abstain form the purchase). In some cases, best-worst experiment can reduce engagement or increase item nonresponse. The paper by Działo (2024) used survey data gathered from students, and it was focused more on the e-commerce impact on customer choices, where the delivery was only one of the options. Hadaś et al. (2024) aimed to assess the attitude of young consumers towards packaging in omnichannel returns. However, these papers used simple descriptive statistics with just a few advanced methods (e.g. chi-squared tests). Witkowski et al. (2024) were focused only on the e-customer preferences for the last-mile delivery to increase customer satisfaction, improve efficiency, and create competitiveness. Our article, on the other hand, presents a broader analysis of delivery options for Polish customers (not only students). Besides, we consider different delivery options without focusing on prices. Delivery prices may not only vary according to different delivery options, but also depend on factors such as the number of items purchased, the purchase value, or special offers.

5. Conclusions

The paper aimed to identify, by means of multi-profile best-worst scaling (BWS), which factors (attributes) affect customer choices of a delivery method while shopping online. The application of BWS allows more information about each choice task to be obtained (customers select the best or the worst profile) compared to discrete choice methods. This leads to more precise estimates with fewer respondents or fewer choices necessary. As in the best-worst methods customers evaluate two profiles, we avoid middle-ground choices that might occur when customers struggle with one choice.

Despite the fact that the literature on last-mile delivery and e-commerce logistics is currently expanding, there is still limited empirical evidence on how consumers jointly evaluate multiple delivery-related attributes when faced with real life choices. Most existing studies focus on single attributes or apply descriptive or discrete choice approaches that do not fully capture the relative trade-offs consumers make between the delivery time, place, payment method and the shopping venue.

The reason for carrying out this study was to provide a more accurate and preference-based understanding of delivery choices by applying the multi-profile best-worst scaling (BWS) method. This approach enables respondents to simultaneously identify the most and the least preferred delivery profiles, yielding more comprehensive information than standard single-choice tasks. This is important in light of the fact that this area of the Polish e-commerce market is still underexplored, despite its rapid growth and progressing diversification of delivery options.

The paper has identified which factors have key influence on customer choices regarding delivery options. The BWS case 3 (multi-profile method) was used where the conditional logit model was applied under the assumption that customers make their choices according to the MaxDiff model. This model presumes that customers select a pair of items (profiles) i and j from the choice set C, where the i-th item is selected as the best one and the j-th as the worst, and the difference in utility between these two items is the maximum one among all possible utility differences. The R software and `survival` package were used for the model estimation. The results demonstrate that regardless of the type of the purchased item, it is the delivery place and payment method that play a crucial role in customers' choices.

The most important attribute is the possibility of the payment via a gateway, and the second most important one is the option of a delivery by a delivery person or to a parcel locker. Such results may suggest that customers want to pay without using cash and prefer doorstep delivery (by a delivery person) or delivery to a parcel locker (in which case they decide when to pick their purchased item up).

From a practical standpoint, the results of this study might help e-commerce retailers, logistics providers and platform operators offer delivery and payment options that are better aligned with customer preferences. By identifying which combinations of a delivery place, payment method and delivery time shape consumer choices to the largest extent, companies are able to optimise their delivery portfolios, prioritise investments in preferred solutions (such as payment gateways or parcel locker networks), and reduce mismatches between the offered services and the ones in demand. Consequently, our findings might contribute to the higher customer satisfaction, increased conversion rates, and more efficient last-mile logistics planning.

References

Aizaki, H., & Fogarty, J. (2019). An R package and tutorial for case 2 best-worst scaling. *Journal of Choice Modelling*, *32*, 1–21. https://doi.org/10.1016/j.jocm.2019.100171.

Aizaki, H., & Fogarty, J. (2023). R packages and tutorial for case 1 best-worst scaling. *Journal of Choice Modelling*, *46*, 1–23. https://doi.org/10.1016/j.jocm.2022.100394.

Auger, P., Devinney, T. M., & Louviere, J. J. (2007). Using best-worst scaling methodology to investigate consumer ethical beliefs across countries. *Journal of Business Ethics*, *70*, 299–326. https://doi.org/10.1007/s10551-006-9112-7.

Bakar, R., Fauziyah, N., & Rahmat, A. (2025). Do Consumers Perceive Impulsive Buying and Pain of Payment? E-Commerce Transactions Using Pay Later, E-wallet, and Cash-On-Delivery. *Gadjah Mada International Journal of Business*, *27*(1), 31–59. https://doi.org/10.22146/gamaijb.81568.

Basch, C. H., Yousaf, H., & Hillyer, G. C. (2025). Online purchasing options for GLP-1 agonists: Accessibility, marketing practices, and consumer safety concerns. *Journal of Medicine, Surgery, and Public Health*, *5*, 1–5. https://doi.org/10.1016/j.glmedi.2025.100183.

Bauer, R., Menrad, K., & Decker, T. (2015). Adaptive Hybrid Methods for Choice-Based Conjoint Analysis: A Comparative Study. *International Journal of Marketing Studies*, *7*(1), 1–14. https://doi.org/10.5539/ijms.v7n1p1.

Bauerová, R. (2018). Consumers' Decision-Making in Online Grocery Shopping: the Impact of Services Offered and Delivery Conditions. *Acta Universitatis Agriculturae et Silviculturae Mendelianae Brunensis*, *66*(5), 1239–1247. https://doi.org/10.11118/actaun201866051239.

Brand, B. M., & Koplin, C. S. (2023). Effective return prevention measures in the post-purchase stage: a best-worst scaling approach. *Marketing ZFP*, *45*(1), 30–47. https://doi.org/10.15358/0344-1369-2023-1-30.

Chodak, G. (2024). *Multi-criteria Evaluation of Assortment and Suppliers in E-commerce*. Palgrave Macmillan Cham. https://doi.org/10.1007/978-3-031-78716-4.

Cohen, E. (2009). Applying best-worst scaling to wine marketing. *International Journal of Wine Business Research*, *21*(1), 8–23. https://doi.org/10.1108/17511060910948008.

Dias, E. G., de Oliveira, L. K., & Isler, C. A. (2021). Assessing the Effects of Delivery Attributes on E-Shopping Consumer Behavior. *Sustainability*, *14*(1), 1–19. https://doi.org/10.3390/su14010013.

Działo, P. (2024). Wpływ handlu elektronicznego na wybory konsumentów [master's thesis, Jagiellonian University in Kraków].

Finn, A., & Louviere, J. J. (1992). Determining the Appropriate Response to Evidence of Public Concern: The Case of Food Safety. *Journal of Public Policy & Marketing*, *11*(2), 12–25. https://doi.org/10.1177/074391569201100202.

Green, P. E. (1974). On the design of choice experiments involving multifactor alternatives. *Journal of Consumer Research*, *1*(2), 61–68. https://doi.org/10.1086/208592.

Green, P. E., Krieger, A. M., & Agarwal, M. K. (1991). Adaptive Conjoint Analysis: Some Caveats and Suggestions. *Journal of Marketing Research*, *28*(2), 215–222. https://doi.org/10.1177/002224379102800208.

Green, P. E., & Srinivasan, V. (1990). Conjoint analysis in marketing: New developments with implications for research and practice. *Journal of Marketing*, *54*(4), 3–19. https://doi.org/10.2307/1251756.

Hadaś, Ł., Domański, R., Wojciechowski, H., Majewski, A., & Lewandowicz, J. (2024). The Role of Packaging in Sustainable Omnichannel Returns – The Perspective of Young Consumers in Poland. *Sustainability*, *16*(6), 1–18. https://doi.org/10.3390/su16062231.

Helveston, J. (2024). *logitr: Logit Models w/Preference & WTP Space Utility Parameterizations*. https://cran.r-project.org/web/packages/logitr/index.html.

Kotler, P., & Keller, K. L. (2016). *Marketing Management* (15th ed.). Pearson Education.

Koyuncu, C., & Bhattacharya, G. (2004). The impacts of quickness, price, payment risk, and delivery issues on on-line shopping. *The Journal of Socio-Economics*, *33*(2), 241–251. https://doi.org/10.1016/j.socec.2003.12.011.

Kumar, S., Pandey, S., & Bhatt, U. (2025). On Enhancing E-Commerce Shipping Policies with Blockchain and Recommender Systems. *SN Computer Science*, *6*(2). https://doi.org/10.1007/s42979-025-03687-x.

Kumar, V., Sindhwani, R., Zhang, J. Z., & Gaur, J. (2024). Optimizing short food supply chains through understanding consumer preferences for organic foods via e-commerce platforms and last-mile logistics. *British Food Journal*, *127*(5), 1788–1809. https://doi.org/10.1108/BFJ-05-2024-0507.

Kunharyanto, S. A., Mayasari, R., & Oktaviana, D. (2025). Optimization in Routing and Vehicle Selection for E-commerce Last Mile Logistics: Bibliometric Analysis. *Acta Informatica Pragensia*, *14*(1), 174–190. https://doi.org/10.18267/j.aip.257.

Lee, J. A., Soutar, G. N., & Louviere, J. (2007). Measuring values using best-worst scaling: The LOV example. *Psychology & Marketing*, *24*(12), 1043–1058. https://doi.org/10.1002/mar.20197.

Louviere, J. J., Flynn, T. N., & Marley, A. A. J. (2015). *Best-Worst Scaling. Theory, Methods and Applications*. Cambridge University Press. https://doi.org/10.1017/CBO9781107337855.

Louviere, J. J., Lings, I., Islam, T., Gudergan, S., & Flynn, T. N. (2013). An introduction to the application of (case 1) best-worst scaling in marketing research. *International Journal of Research in Marketing*, *30*(3), 292–303. https://doi.org/10.1016/j.ijresmar.2012.10.002.

Lusk, J. L., & Briggeman, B. C. (2009). Food Values. *American Journal of Agricultural Economics*, *91*(1), 184–196. https://doi.org/10.1111/j.1467-8276.2008.01175.x.

Luttermann, S., Buschmann, C., Freitag, M., Kotzab, H., Tiggemann, J., Trapp, M., & Weßling, M. (2021). *What is the right home delivery option for your online shopping?*. In U. Buscher, R. Lasch & J. Schönberger (Eds), *Logistics Management. Lecture Notes in Logistics* (pp. 137–150). Springer. https://doi.org/10.1007/978-3-030-85843-8_9.

Massey, G. R., Wang, P. Z., Waller, D. S., & Lanasier, E. V. (2015). Best-worst scaling: A new method for advertisement evaluation. *Journal of Marketing Communications*, *21*(6), 425–449. https://doi.org/10.1080/13527266.2013.828769.

McFadden, D. (1974). Conditional logit analysis of qualitative choice behavior. In P. Zarembka (Ed.), *Frontiers in Econometrics* (pp. 105–142). Academic Press. https://eml.berkeley.edu/reprints/mcfadden/zarembka.pdf.

Nguyen, D. H., de Leeuw, S., Dullaert, W., & Foubert, B. P. J. (2019). What Is the Right Delivery Option for You? Consumer Preferences for Delivery Attributes in Online Retailing. *Journal of Business Logistics*, *40*(4), 299–321. https://doi.org/10.1111/jbl.12210.

Pascoe, M., Wright, O., & Winzar, H. (2017). Using best-worst scaling to reveal perceived relative importance of website attributes. *Asia Pacific Journal of Marketing and Logistics*, *29*(2), 393–408. https://doi.org/10.1108/APJML-08-2015-0130.

Pfaff, L. (2021). *Comparison of Menu-Based Conjoint Methods for Different Questionnaire Designs* [Master thesis, Erasmus University Rotterdam]. https://thesis.eur.nl/pub/56915.

Radyi, S. A. M., Ridzwan, R., Mohamad, N. M., & Rahman, M. A. A. (2024). Influences on Generation Z's Purchasing Decision-Making on E-Commerce Platforms: Beyond Products and Website Design. *International Journal of Academic Research in Business & Social Sciences*, *14*(12), 2457–2469. https://doi.org/10.6007/IJARBSS/v14-i12/24203.

Raghavarao, D., & Padgett, L. V. (2005). *Block Designs. Analysis, Combinatorics and Applications* (Vol. 17). World Scientific Publishing.

Rausch, T. M., Baier, D., & Wening, S. (2021). Does sustainability really matter to consumers? Assessing the importance of online shop and apparel product attributes. *Journal of Retailing and Consumer Services*, *63*, 102681. https://doi.org/10.1016/j.jretconser.2021.102681.

Rotem-Mindali, O., & Salomon, I. (2007). The impacts of E-retail on the choice of shopping trips and delivery: Some preliminary findings. *Transportation Research Part A: Policy and Practice*, *41*(2), 176–189. https://doi.org/10.1016/j.tra.2006.02.007.

Rybicka, A. (2013). Od conjoint analysis do metod wyborów opartych na menu. *Zeszyty Naukowe UE w Krakowie*, (916), 13–23. https://doi.org/10.15678/krem.735.

Tam, K. Y., & Ho, S. Y. (2005). Web Personalization as a Persuasion Strategy: An Elaboration Likelihood Model Perspective. *Information Systems Research*, *16*(3), 271–291. https://doi.org/10.1287/isre.1050.0058.

Therneau, T. M., Lumley, T., Atkinson, E., & Crowson, C. (2024). *survival: Survival Analyisis*. https://github.com/therneau/survival.

Train, K. E. (2009). *Discrete Choice Methods with Simulation* (2 ed.). Cambridge University Press. https://doi.org/10.1017/CBO9780511805271.

Wahyudien, M. A. N., Ahistasari, A., Kayatun, S. N., Gani, M., & Wattihelu, S. A. (2024). Selection of Delivery Services Based on Customer Relationship Management and SAW Method. *Journal of Engineering & Management in Industrial System*, *12*(2), 135–142. https://jemis.ub.ac.id/index.php/jemis/article/view/19637.

Witkowski, J., Skowrońska, A., Cheba, K., & Baranicka, A. (2024). Comparative analysis of study results on e-commerce customer preferences in last-mile delivery in Poland. *Gospodarka Materiałowa i Logistyka. Material Economy and Logistics Journal*, *76*(1), 15–27. https://doi.org/10.33226/1231-2037.2024.1.2.

Yang, S.-H., Panjaitan, B. P., Ujiie, K., Wann, J.-W., & Chen, D. (2021). Comparison of food values for consumers' preferences on imported fruits and vegetables within Japan, Taiwan, and Indonesia. *Food Quality and Preference*, *87*, 1–10. https://doi.org/10.1016/j.foodqual.2020.104042.

Zwerina, K. (1997). *Discrete Choice Experiments in Marketing. Use of Priors in Efficient Choice Designs and Their Application to Individual Preference Measurement*. Springer-Verlag Berlin Heidelberg. https://doi.org/10.1007/978-3-642-50013-8.