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Supplier selection in emerging market economies: a discrete choice analysis

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Abstract: This study presents the perceived importance of different supplier attributes for managers' choice of suppliers in emerging market economies. We analyze the supplier selection process based on multiple attributes categorized into six groups: quality, cost, delivery, product, service, and business. Empirical data for this study was collected from 163 corporate executives in the automotive and fast-moving consumer goods industries operating in Poland and India. A two-part survey was conducted; the first part consisted of a Likert scale set of questions aimed at determining the perceived importance of supplier attributes. The second part of the survey was a discrete choice experiment that examined the actual choices of experimental supplier profiles made by executives. Comparing our results to previous works in this domain, we find that the importance of the cost attribute has decreased over the past two decades, whereas the relevance of delivery and product has increased. Each of the six supplier attributes was broken down into sub-attributes, which provided us with an insight into the decision-making process. The results indicate that with respect to delivery, delivery lead time, responsiveness to demand fluctuations, and compliance with due date had a significant effect on executives' decisions. At the same time, new product availability and product range played crucial role amongst product attributes. Finally, the dataset was split into different sub-groups, based on the two industries and two countries analyzed, to examine industrial and cultural differences.

Keywords: supplier selection, vendor selection, purchasing, supply chain management, conjoint analysis, stated preferences, discrete choice experiment

JEL codes: C01, C44, C90

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1 Introduction

In the past four decades, the supplier selection process has received considerable attention in the operations management literature. Miller et al. (1981) was among the first to identify supplier selection as an important strategic operating choice. Understanding supply chain-related decisions is widely recognized in business management as an important process for improving a firm's competitive position. Managerial supplier choices must be consistent with corporate strategy to ensure effective operations management. In addition, the issue of supplier selection has become even more critical as the use of extended enterprise concepts has increased among a wide range of firms across different industries.

Dickson (1966) identified over twenty supplier attributes that managers consider when choosing a supplier. Since then, a multitude of conceptual and empirical articles exploring supplier selection have appeared (Weber et al., 1991). The conceptual articles by Ansari and Modarress (1986), Benton and Krajewski (1990), Browning et al. (1983), Burton (1988), Jackson (1983), and Kraljic (1983) are all examples of publications emphasizing the strategic importance of the supplier selection process. These works particularly highlight the trade-off among quality, cost and delivery performance measures within the selection process. The supplier selection literature is also rich in terms of conceptual models, decision support systems, simulation studies, and empirical analyses related to the vendor evaluation (Pearn et al., 2004; Bhutta and Huq, 2002; Chan, 2003; Chan and Chan 2004; Onesime et al., 2004; Basnet and Leung, 2005; Valluri and Croson, 2005; Carter and Jennings, 2004; Kamann and Bakker, 2004; Lin et al., 2005).

While much conceptual and empirical work appears in the supplier selection literature, only a few articles have studied how decision-makers actually choose suppliers. Much of the empirical research focuses on the results of the perceived importance of key attributes in supplier selection. Selecting among several suppliers usually involves choosing from a trade-off between several attributes, for if one supplier were to excel in every attribute, no decision analysis would be necessary. Market utility-based approaches such as discrete choice analysis (DCA) can be used to assess the relative weights of different criteria in various managerial decision-making settings (Ben-Akiva and Lerman, 1991; McFadden, 1986; Louviere et al., 2001). These methods have seen wide applications in many social sciences including marketing, transportation planning, environmental and resource economics, service design, and operations management (Green and Krieger, 1996; Pullman and Moore, 1999; Pullman et al., 2001; Verma et al., 2001, Hanley and Czajkowski, 2019). Examples of DCA applications in operations management include product line decisions (Yano and Dobson, 1998), optimal service design (Verma et al., 2001), and operations capacity planning (Pullman and Moore, 1999).

Although market utility-based approaches in general, and discrete-choice models in particular, are effective in operations management, little research work has been done to integrate those techniques into the supplier selection problem. Perhaps one of the earliest and most prominent studies in this field is the discrete choice analysis performed by Verma and Pullman (1998). They find that the stated preferences across a purchasing manager's relevant criteria for supplier selection do not necessarily coincide with their actual supplier choices. Their results indicate that although managers say that quality is the most important attribute for a supplier, they actually choose suppliers based largely on cost and delivery performance. Li et al. (2006) extended the use of DCA in the supplier selection literature by comparing the attributes of an existing supplier to that of a new supplier. These authors also extended the theoretical framework to include supplier switching inertia. They confirmed the existence of switching inertia and revealed the competitive asymmetry between current and new suppliers from a demand-side perspective. Van der Rhee et al. (2009) explored how executives and managers trade-off amongst various competitive dimensions, such as cost, delivery performance, flexibility, and value-added service/support when selecting a supplier for raw materials, with the condition that minimum acceptable quality is guaranteed. They tested the suggested model against data collected across several European countries.

Our study contributes to this evolving literature by in investigating the supplier selection process in the emerging market economies. We employ a two-stage experimental process to understand the differences between the perceived importance of supplier attributes and the actual choices of suppliers made by decision-makers. We expanded the list of relevant supplier attributes, based recent developments in the academic and practitioner literature, as well as several rounds of expert interviews. Furthermore, to the best of our knowledge, this is the first attempt to test the actual choices of suppliers for two significantly distant developing markets. Finally, we compared the results of our two-stage process across the fast-moving consumer goods (FMCG) and automotive industries. With respect to methodological aspects of this study, Data from a Likert scale questions were used for the first stage of our experiment, followed by a discrete choice analysis. Unlike previous works, we applied the mixed logit (MXL) model to overcome heterogeneity issues between our data subsets, as well as to take into account the correlation between supplier attributes.

The remainder of the paper is structured as follows. Section 2 begins with an overview of the two-stage process used for this study, followed by the list of experimental attributes and the choice design. We then provide information on data collection and the econometric framework applied in our analysis. Section 3 summarizes the results of the Likert scale questions and the DCA experiment, and Section 4 offers a discussion. Section 5 concludes with a summary of findings and provides recommendations for future work.

2 Methods

An empirical study was conducted to investigate the supplier selection process in emerging markets. To explore the research objectives, we designed a two-stage experimental study using a combination of Likert scale questions and a discrete choice analysis (DCA). The respondent sample consisted of corporate executives working in the automotive and fast-moving consumer goods industries in both Poland and India. Each industry relies heavily on external trading partners and has a strong presence in both countries.

2.1 Two-stage process

As mentioned earlier, our respondents participated in a two-part survey. In the first part of the survey, Likert scale questions were used to examine the perceived importance of different supplier attributes. In total, each respondent was asked to evaluate the importance of twenty-seven attributes, grouped into six categories, ranging from 1 (least important) to 5 (most important). The results of the Likert part of the survey were used to find which of the six main attributes had the highest average rating. We were also able to compare these results to those of the second stage and find out whether the seemingly important attributes actually play an important role in the supplier selection process.

In the second part of the survey, DCA was used to evaluate the choices of experimental supplier profiles selected by our respondents. Past research in econometrics, marketing, and social sciences has shown that DCA is an effective methodology for analyzing choices in complex situations where multiple attributes influence decision-making (McFadden, 1986; Ben-Akiva & Bierlaire, 1999). When making a choice from a set of alternatives, DCA can be utilized to systematically identify the relative weights of different attributes when assessing the tradeoffs between them. DCA involves requiring the respondents to choose from multiple experimental profiles that were created for this purpose and were based on the attribute levels assigned to each profile. The experimental alternatives are normally created according to pre-determined experimental design procedures allowing the researcher to control the levels of independent variables. The distribution of the dependent variable is based on choices made by the respondents. The conditional probability of choosing an alternative can be determined using an econometric framework called mixed logit (MXL) model. Later in this article, we present further details on the econometric setup used in our study.

2.2 Supplier attributes and experimental design

Identification of determinant attributes is the first step of the experimental design for a DCA. Louviere et al. (2000) suggest that reviews of academic and practitioner literature combined with qualitative surveys, interviews, case studies and focus groups must be used to build a list of relevant attributes for a given experimental design. They also emphasize ensuring that all the salient attributes are determined and expressed in terms that are well understood by the decision-makers. Furthermore, it is necessary to understand which attributes could be re-expressed and recombined to keep the set exhaustive and, at the same time, as concise as possible. That would help make the experiment both realistic and tractable.

In order to develop a comprehensive list of supplier attributes that could be comparable across countries and industries, we started with the existing academic and practitioner literature. This allowed us to create an initial list of attributes which we ran through several rounds of expert interviews. We had a chance to collect both supply- and demand-side perspective from corporate executives working in purchasing, sales, product development, supply chain management, and cost engineering functions. For example, feedback was collected from both purchasing managers working at automotive original equipment manufacturers (OEMs) and sales managers working at automotive suppliers. Moreover, experts from both European and Asian continents were interviewed to inform this process from a wide spectrum of geographical perspectives. Based on the first round of individual feedback, the list of suppliers was adjusted in terms of content, comprehensiveness, and wording. The updated list was presented in two further rounds (one additional round of individual feedback and one round of group discussion) for yet additional feedback. The final list consists of twenty-seven supplier attributes grouped into six broad categories: quality, cost, delivery, product, service, and business performance. The comprehensive list of all twenty-seven attributes is presented in Table 1.

Table 1. Six main attributes and all sub-attributes

Quality	Cost	Delivery	Product	Service	Business
Internal quality control rejection rate	Purchase price	Compliance with due date	Product range	Reliability	Financial stability
Customer review ratings	Logistics and other costs	Delivery lead time	New product availability	Response time	Reputation and position in industry
	Inelasticity of payment plans	Flexibility for change in delivery date	Availability of add-on features	Convenience of communication system	Level of technology and innovations
	Lack of promotions	Flexibility for special requests	Usage of recycled materials	Attitude and professionalism	Proximity of geographical location
	Level of detail in cost itemization	Responsiveness to demand fluctuations	Availability of ergonomic features	Convenience of warranty/claim policy	Risks associated with foreign trade

After identifying the relevant attributes, a set of alternative supplier profiles was generated using experimental design procedures. Each experimental profile represents a combination of different values for each supplier attribute. Louviere et al. (2000) note that in order to limit the number of experimental profiles, most practical conjoint studies involving multiple alternatives rely on the fractional factorial design procedure. According to Verma & Pullman (1998), most researchers attempt to limit the number of profiles to 16 or less to prevent degradation of response quality. In order to limit the number of profiles, researchers usually apply two possible techniques: limit the number of attributes and attribute levels and use fractional factorial designs capable of estimating all main effects.

A combination of both techniques was utilized for this study. First, only two levels (*-1* (low) and *+1* (high)) of each supplier attribute were considered, given the computational complexity for twenty-seven attributes. Furthermore, similar to the previous efforts in this field, we applied a fractional factorial design procedure to develop 64 orthogonal supplier profiles, which would allow for estimating the main effects for all attributes (Louviere e al., 2000). In order to make the decision as realistic as possible, a full-profile approach was used, i.e., no supplier attributes were omitted, and each profile described a certain combination of all twenty-seven attributes (Green & Srinivasan, 1990). Given that it is unrealistic for each respondent to systematically evaluate 64 supplier profiles with twenty-seven attributes each, we used blocking to split the core set of profiles into statistically equivalent subgroups. Further details on this approach can be found in the textbook by Louviere et al. (2000), which provides a comprehensive overview of discrete choice experiments including fractional factorial designs and blocking.

Using the above-mentioned procedure, the initial 64 profiles were then divided into four statistically equivalent sets of 16 profiles each. Each respondent was randomly assigned to one of the four subsets and asked to respond to 16 choice tasks. Each of the 16 profiles included in choice tasks was paired with its foldover design, i.e., with an alternative supplier profile with opposite attribute levels compared to the original design. For example, a supplier profile with *-1* (low) level for each attribute would be paired with the profile that has *+1* (high) level for all the attributes. For each choice task, the respondents were asked to choose the original supplier, the alternative supplier, or neither. A full description of all supplier profiles and presentation of the detailed experimental design-matrix are avoided in this paper, given the large number of supplier attributes and the resulting complexity of the design. However, the experimental-design procedure followed was consistent with the previous works in the supplier selection domain.

Both stages of the choice experiment were pre-tested with a selected group of respondents from each subset. Based on a round of feedback, the structure and the design of the choice tasks were optimized to make them as clear and user-friendly as possible. Our main concern was that the choice tasks would be too complex and confusing, given the large number of attributes. However, the overall feedback from the qualitative pretesting with selected executives was that the trade-off between multiple attributes is rather close to reality, and that complexity of supplier selection is unavoidable in practice.

2.3 Data collection

The data was collected using computer-assisted web-based self-interviewing (CAWI) during the second half of 2019. The invitation to participate was sent to corporate executives in both Poland and India who were working in the automotive and FMCG industries (chosen using NAICS codes 31-32 and 336, respectively, combined with input from industry experts). Each target company employed between 500-999 people and had presence in multiple countries. From the target population of 824 executives, slightly more than 500 executives agreed to participate in the survey. Only 32% of those eventually completed the entire survey, resulting in a final response rate of 20%.

Indeed, the data collection for this study was rather a time-consuming process. In addition to the supplier selection tasks, the survey also included demographic questions about the respondents, such as information on age and gender. (A table appears in a later section that shows the number of respondents by country and industry who filled out a complete survey.) The main descriptive statistics for our sample is broken down by country and industry in a later section.

2.4 Data analysis procedure

The data collected from the Likert scale questions was used as a measure of relative perceived importance of supplier attributes. These statistics were averaged over the six main attribute categories, allowing them to be ranked based on average perceived importance. At the same time, the Likert scale results were compared to the effects found in the DCA on attribute level. This was designed to allow a comparison between the perceived relevance of supplier attributes and the actual choices made by the respondents. Furthermore, the data collected from the Likert scale questions was averaged over each subset of respondents (FMCG Poland, FMCG India, automotive Poland, automotive India). This gave us the opportunity to compare industry- and country-related differences in the perceived importance of attributes. For modeling purposes all the supplier attributes were labeled using short names, which are presented in Table 2.

Within the DCA framework, the conditional probability of choosing an alternative in a choice task can be analyzed with an econometric model called mixed logit (MXL). MXL is normally used to overcome the limitations of the standard multinomial logit (MNL) as it describes the heterogeneity in the population by the distribution of the individual-level preferences rather than relying on average preferences. MXL allows for both random taste variation and unrestricted substitution patterns (Revelt and Train 1998). In other words, the invidiual-level parameters are assumed to vary from one individual to another in the MXL setup. When different individuals are expected to have different preferences, models that facilitate estimating the individual-level coefficients usually fit the data better and make more accurate predictions than sample-level models (Train, 2009; Rossi et al., 2012). MXL has been used in advanced discrete choice research due to its flexibility and ability to approximate any random utility model (McFadden and Train, 2000).

Table 2. List of attributes characterizing each alternative

	Attribute	**Short name**
Quality	Internal quality control rejection rate	quality1
	Customer review ratings	quality2
Cost	Purchase price	cost1
	Logistics and other costs	cost2
	Inelasticity of payment plans	cost3
	Lack of promotions	cost4
	Level of detail in cost itemization	cost5
Delivery	Compliance with due date	delivery1
	Delivery lead time	delivery2
	Flexibility for change in delivery date	delivery3
	Flexibility for special requests	delivery4
	Responsiveness to demand fluctuations	delivery5
Product	Product range	product1
	New product availability	product2
	Availability of add-on features	product3
	Usage of recycled materials	product4
	Availability of ergonomic features	product5
Service	Reliability	service1
	Response time	service2
	Convenience of communication system	service3
	Attitude and professionalism	service4
	Convenience of warranty/claim policy	service5
Business	Financial stability	business1
	Reputation and position in industry	business2
	Level of technology and innovations	business3
	Proximity of geographical location	business4
	Risks associated with foreign trade	business5

This analysis applied and utilized the principles and the notation of the MXL model developed by Akinc and Vandebroek (2017). The decision-maker faces a choice task among J alternatives. The utility of individual n from alternative k is specified as

$$U_{ksn} = \sum_{l=1}^{L} \beta_{nl} x_{ksnl} + \varepsilon_{ksn} \tag{1}$$

where L is the total number of explanatory variables, n is the individual, k is the alternative, s is the choice situation, x_{ksnl} is an explanatory variable, β_{nl} is a parameter of the l^{th} explanatory variable for individual n and ε_{ksn} is an unobserved random term. Given that homogeneity in the preferences of respondents from different industries and countries is unlikely, the possibility of taste variations should be introduced. The individual-level parameters, β_n , associated with the attributes are assumed to vary according to a probability distribution $\beta_n \sim f(\beta_n |\mu, \Sigma)$.

In the sequel, we will assume that the heterogeneity distribution $f(\beta_n |\mu, \Sigma)$ is a multivariate normal distribution. Conditional on β_n, the probability that individual n chooses alternative k in choice set s is

$$p_{ksn}(\beta_n) = \frac{exp(x'_{ksn}\beta_n)}{\sum_{i=1}^{k} exp(x'_{isn}\beta_n)} \tag{2}$$

where x_{ksn} is an L-dimensional vector characterizing the attribute levels of alternative k in choice set s for respondent n with L number of coefficients in the model. The choice is stored in the variable y_{ksn}, a binary variable that equals one if respondent n chooses alternative k in choice set s and zero otherwise. Let y_n contain all the choices from respondent n corresponding to all S choice sets. The probability, unconditional on β_n, of a respondent n's choices y_n is

$$\pi_n(y_n|\mu, \Sigma) = \int_{\beta_n}^{\cdot} (\prod_{s=1}^{S} \prod_{k=1}^{K} [p_{ksn}(\beta_n)]^{y_{ksn}})\, f(\beta_n|\mu, \Sigma)\, d\beta_n \tag{3}$$

The MXL model takes into account the correlation of the probabilities for a single respondent in multiple choices and is therefore also called the panel mixed logit model. The log-likelihood of the MXL model is

$$\begin{aligned} LL(\mu, \Sigma|\mathrm{y}) &= \sum_{n=1}^{N} \ln\left(\pi_n(y_n|\mu, \Sigma)\right) \\ &= \sum_{n=1}^{N} \ln\left[\int_{\beta_n}^{\cdot} (\prod_{s=1}^{S} \prod_{k=1}^{K} [p_{ksn}(\beta_n)]^{y_{ksn}})\, f(\beta_n|\mu, \Sigma)\, d\beta_n\right] \end{aligned} \tag{4}$$

where $y = [y_1, \ldots, y_N]$ denotes the matrix of choices from all N respondents.

The mean taste parameter coefficients represent the average value that respondents place on each attribute, while the variance and covariance values reflect the heterogeneity of preferences across the population. In this case, the parameters are allowed to be correlated, given that there are several attributes per category (quality, cost, delivery, business, product, service, business performance), and that the importance of individual attributes is likely to be associated with the importance of related attributes. Estimating the mixed logit model always comes at the expense of increasing the number of estimated parameters, which is why we empirically show its superior fit compared to its restricted versions - the multinomial logit model (which assumes that β_n=β, i.e. constant across respondents) and the mixed logit model (with uncorrelated random effects). The model's specification allows for heterogeneous preferences at the individual level, which is the highest possible level of disaggregation.

Obtaining individual-level parameter estimates allows for investigating how their mean values differ across individuals from different countries and industries to infer cross-industry and cross-country differences.

Determining the relative importance for each attribute provides valuable insights on the influence that each attribute has on the decision-making process. As all attributes have two levels (high/low) and the beta parameter estimates reflect the utility of high level of each attribute relative to low (whose utility is set to zero), the importance ranking of attributes corresponds to the ranking of beta parameter estimates (Orme, 2002). The average importance of the six attribute categories (quality, cost, delivery, product, service, business performance) is ranked by averaging out parameter estimates within each category.

3 Results

This section describes the main results of data analysis based on our two-stage procedure. The results are presented for the full set of respondents, followed by subset-specific outputs. In the beginning, we provide a description of the main characteristics of our respondents, broken down by country and industry.

3.1 Descriptive statistics

From the 163 respondents who completed the whole survey, more than 60% were based in India and the rest worked in Poland. In terms of industry mix, more than half of the executives worked in the automotive industry. Table 3 summarizes the above-mentioned statistics for the whole respondent pool.

Table 3. Number of respondents.

	FMCG	Automotive	Total
Poland	27	38	**65**
India	45	53	**98**
Total	**72**	**91**	**163**

Further characteristics on our sample are shown in Figures 1 and 2. Figure 1 shows the male/female distribution for the FMCG and automotive industries. In both industries, about 80% of respondents were males and 20% were females. However, in FMCG, the percentage of women is a slightly higher compared to the automotive industry. This is rather unsurprising, given the common knowledge on existing concerns and efforts taken up for increasing the percentage of women announced by different OEMs in recent years. Figure 2 shows the age distribution of survey respondents in both industries. Majority of executives belonged to the 30-44 age group. This implies that most of our respondents were mid-career professionals. At the same time, the average age in FMCG seems to be lower compared to the automotive industry. One possible explanation to this difference could be the fact that many consumer-packaged goods companies, especially in developing countries, prioritize the search for young high-skilled talent via different future leader programs. (See the Table 9 in the Appendix 1 for more detailed descriptive statistics.)

Figure 1. Gender distribution of respondents across industries.

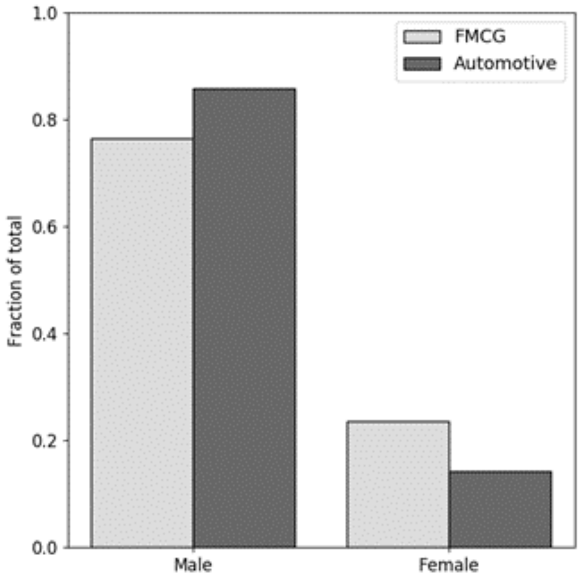
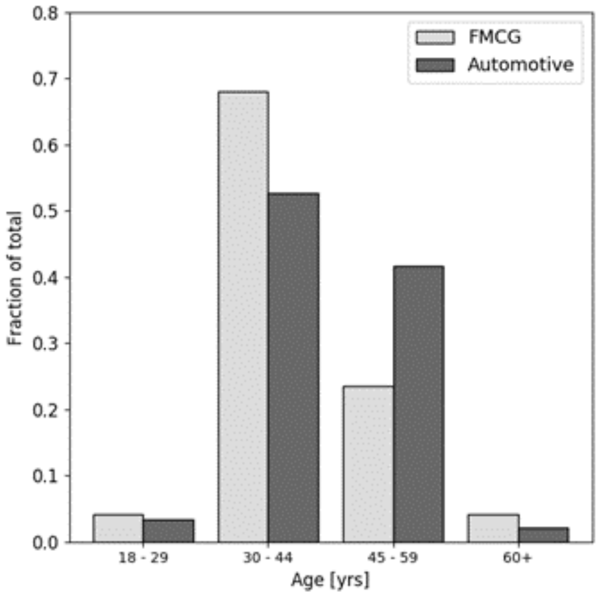


Figure 2. Age distribution of respondents across industries.



3.2 Perceived importance of attributes

As explained in the Methods section, Likert scale questions were used to explore the perceived importance of various supplier attributes. As mentioned earlier, the twenty-seven supplier attributes were grouped into six main categories: quality, cost, delivery, product, service, and business performance. Table 4 shows the rank of each attribute category based on the average rating given to the attributes within each category. Further columns in the table indicate the actual average ratings combined with standard deviations. For example, since the average rating of the service attribute is the highest with 3.8 ± 0.6, this category is assigned rank I. Alternatively, median ratings can be compared when dealing with Likert scale type questions. Therefore, we included the median perceived importance for the six attribute categories. The data shown in Table 4 represents the results for the full set of respondents.

Table 4. Descriptive statistics for Likert scale questions for all respondents.

	Rank based on average rating	Average rating ± standard deviation	Median
Service	I	3.8 ± 0.6	4
Product	II	3.6 ± 0.2	4
Quality	III	3.5 ± 0.7	4
Cost	IV	3.3 ± 0.6	3
Business	V	3.2 ± 0.4	3
Delivery	VI	3.1 ± 0.4	3

The results show that corporate executives perceive service, product and quality (in order of importance) to be the most relevant attributes, while delivery is rated to be the least important across the other attribute categories. Past research in supplier selection (Verma & Pullman, 1998) has shown that executives particularly emphasize quality, followed by delivery and cost. The most salient differences between previous works and our results in the perceived importance of different attributes are discussed further in the next section.

Table 5 is built upon Table 4 with the main difference being that the average assigned rating per attribute category is shown for each subset of respondents. There are noticeable differences between industries and countries in terms of the perceived importance of attributes, with the delivery attribute creating significant discrepancies. For comparison, it is assigned the second highest average importance in the automotive industry in Poland but is assigned the lowest average rating by the FMCG respondents in India.

Figure 3 suggests an alternative way of presenting the information from Table 5. Further differences become apparent when comparing the subsets in groups (i.e., combined by industry or country). For example, the automotive industry assigns a much higher rating to delivery compared to FMCG. Polish respondents from both industries assign higher ratings to service than their Indian counterparts. Furthermore, the large standard deviation of the quality rating for FMCG (across both countries) is quite remarkable compared to the relatively smaller deviation in the automotive industry.

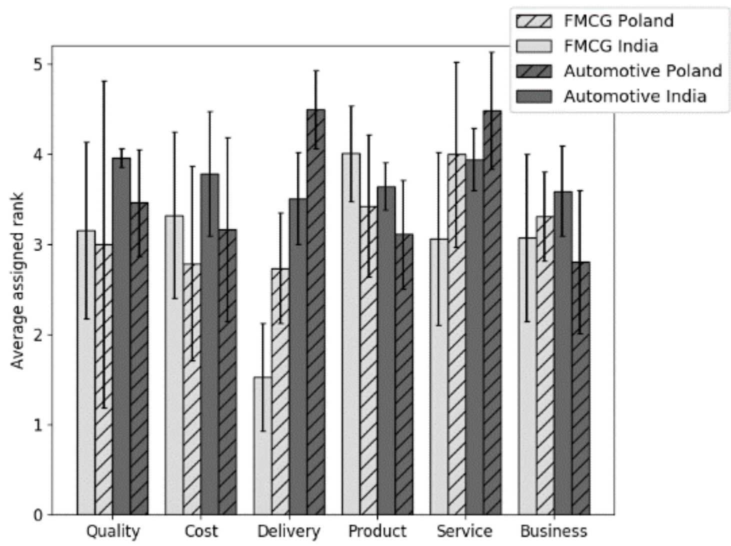
Table 5: Descriptive statistics for Likert scale questions for each subset of respondents.

	FMCG				**Automotive**			
	Poland		**India**		**Poland**		**India**	
	Rank	**Rating***	**Rank**	**Rating***	**Rank**	**Rating***	**Rank**	**Rating***
Quality	IV	3.0 ± 1.8	II	3.2 ± 1.0	III	3.5 ± 0.6	**I**	**4.0 ± 0.1**
Cost	V	2.8 ± 1.1	II	3.3 ± 0.9	IV	3.2 ± 1.0	III	3.8 ± 0.7
Delivery	VI	2.7 ± 0.6	VI	1.5 ± 0.6	II	3.8 ± 0.4	VI	3.5 ± 0.5
Product	II	3.4 ± 0.8	**I**	**4.0 ± 0.5**	V	3.1 ± 0.6	IV	3.6 ± 0.3
Service	**I**	**4.0 ± 1.0**	IV	3.1 ± 1.0	**I**	**4.5 ± 0.6**	II	3.9 ± 0.3
Business	III	3.3 ± 0.5	IV	3.1 ± 0.9	VI	2.8 ± 0.8	IV	3.6 ± 0.5

* *Average rating ± standard deviation*

We now turn to presenting several pairwise comparisons from the overall list of all supplier attributes. Since we are dealing with a large number of attributes across multiple categories, it would be unsurprising to find some correlation between specific attribute pairs. The first example explored in this section compares the development of proximity of geographical location and the risks associated with foreign trade. The idea is to better understand whether the perceived importance for these two attributes moves in the same direction for different subsets.

Figure 3. Average rating for the 6 main attribute categories by subset.



The results for the above-mentioned attributes are summarized in Figure 4. This tow dimensional histogram shows which combination of ratings was chosen most frequently for the subsets of Polish and Indian respondents. Corporate executives in Poland (left panel) most often assigned a higher importance to the risks associated with foreign trade and assigned a relatively lower rating the proximity of geographical location. This could imply that Polish respondents would rather choose a local supplier (if at all) based mostly on economic reasons (import taxes, currency exchange rates, etc.) rather than on the desire to work with local suppliers. The right panel shows that executives in India often assigned relatively low ratings to both attributes.

Figure 4. Ratings of the 'proximity of geographical location' and 'risks associated with foreign trade'. The two panels show respective subsets of the full dataset.

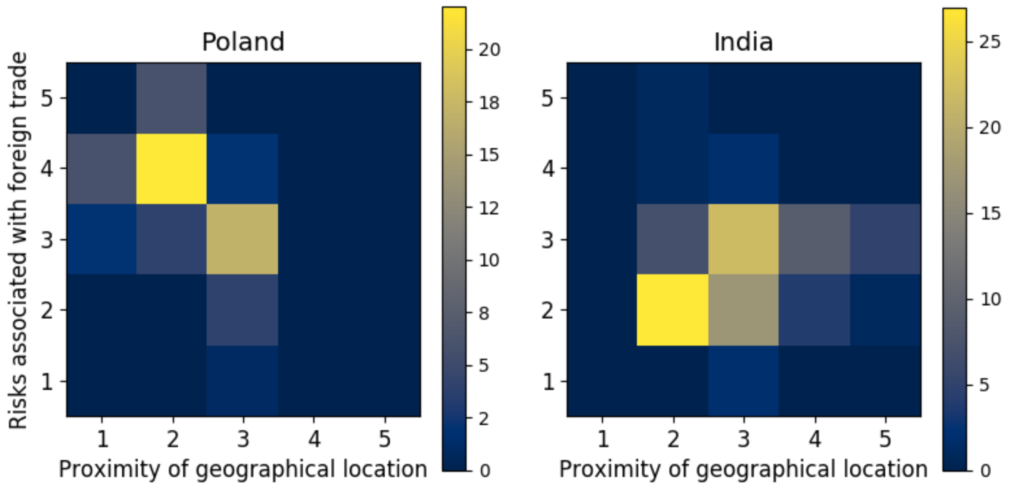
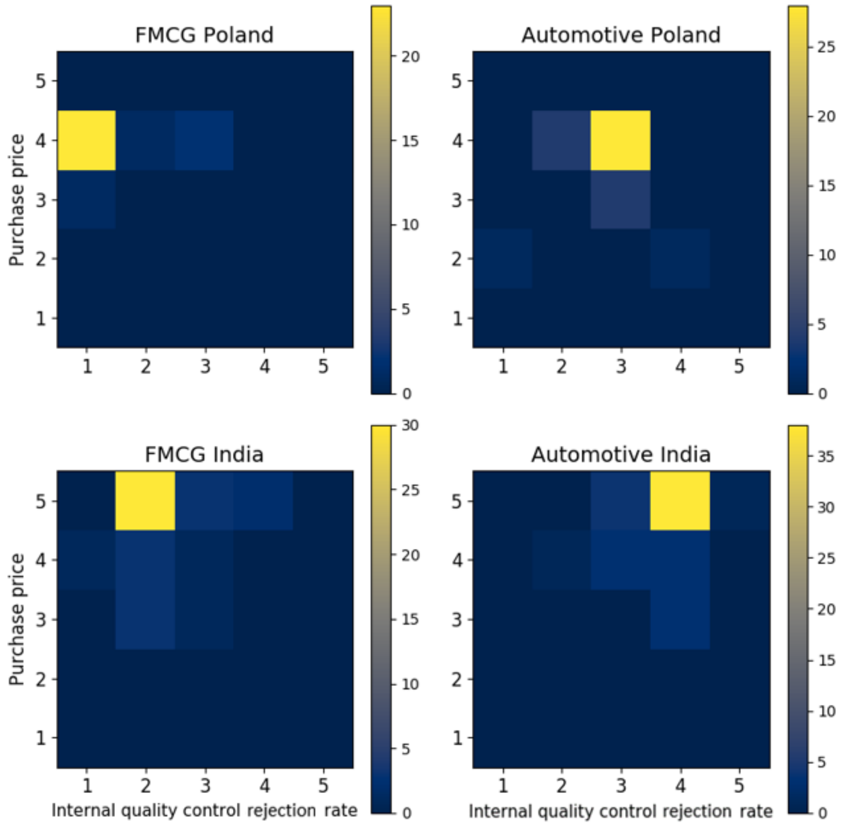


Figure 5 shows another interesting combination of supplier attributes across the different subsets. Several interesting developments are visible with regard to internal quality control approval rate and purchase price. Noticeable differences exist between the FMCG and automotive industries in both countries. In the FMCG industry, purchase price is given a significant weight, and the respondents seem to tolerate a trade-off in quality (in this case, internal quality control approval rate). For the executives working in automotive OEMs, both factors are considered relatively important and no significant trade-offs are expected between these two attributes.

Figure 5. Ratings of 'internal quality control rejection rate' and 'purchase price' across subsets.



3.3 DCA for the supplier choice process

In this section, the results of the discrete choice analysis are presented. First, we compared the multinomial logit model (with fixed parameters), the mixed logit model with uncorrelated parameters and the mixed logit model with correlated parameters built on the whole sample. These results appear in Table 6.

The log-likelihood ratio is higher, and the Akaike information criterion (AIC) is lower for the mixed effect logit models (models 2 and 3). This indicates their superiority to the fixed coefficients model and implying the presence of unobserved heterogeneity among respondents. The model with correlated random parameters (model 3) is not only the one with the highest log-likelihood, but also the most realistic from theoretical perspective as it allows for parameters to be correlated with one another. Further details on the likelihood ratio tests can be found in Appendix 2. The presence of the "neither of these" option in the supplier choice sets was accounted for by using the alternative-specific variable *opt1_2* which equals one when alternatives one and two (supplier profiles in each pair) are chosen and zero when neither is chosen.

Table 6. Parameter estimates of the mixed logit model with correlated parameters and its restricted versions

	Model 1: Multinomial logit			Model 2: Mixed logit (uncorrelated parameters)			Model 3: Mixed logit (correlated parameters)		
	Estimate	Std. Error	p-value	Estimate	Std. Error	p-value	Estimate	Std. Error	p-value
opt1_2	1.676	0.167	0.000	1.563	0.193	0.000	0.899	0.881	0.308
quality1	-0.282	0.050	0.000	-0.336	0.062	0.000	-1.459	0.345	0.000
quality2	0.199	0.051	0.000	0.260	0.063	0.000	0.547	0.280	0.051
cost1	-0.337	0.050	0.000	-0.440	0.063	0.000	-1.526	0.354	0.000
cost2	-0.228	0.051	0.000	-0.297	0.064	0.000	-0.763	0.348	0.028
cost3	-0.155	0.050	0.002	-0.206	0.061	0.001	-1.216	0.333	0.000
cost4	-0.059	0.050	0.234	-0.060	0.060	0.322	-0.730	0.310	0.018
cost5	-0.009	0.049	0.847	-0.030	0.060	0.613	0.167	0.265	0.528
delivery1	0.600	0.050	0.000	0.744	0.065	0.000	2.256	0.351	0.000
delivery2	-0.410	0.050	0.000	-0.514	0.063	0.000	-1.697	0.316	0.000
delivery3	-0.025	0.050	0.613	-0.028	0.061	0.643	-0.259	0.302	0.392
delivery4	-0.261	0.050	0.000	-0.324	0.062	0.000	-0.618	0.334	0.064
delivery5	0.561	0.050	0.000	0.706	0.066	0.000	2.829	0.414	0.000
product1	0.375	0.051	0.000	0.475	0.064	0.000	1.358	0.375	0.000
product2	0.638	0.050	0.000	0.824	0.068	0.000	3.026	0.418	0.000
product3	0.213	0.051	0.000	0.288	0.062	0.000	0.657	0.340	0.053
product4	0.027	0.050	0.593	0.046	0.063	0.462	-0.389	0.290	0.180
product5	-0.005	0.050	0.923	-0.016	0.060	0.795	-0.446	0.276	0.106
service1	0.022	0.050	0.660	0.018	0.061	0.769	0.155	0.310	0.617
service2	0.035	0.050	0.491	0.046	0.061	0.449	-0.387	0.292	0.186
service3	0.004	0.050	0.929	-0.001	0.061	0.985	0.186	0.306	0.542
service4	-0.048	0.050	0.343	-0.068	0.062	0.268	-0.305	0.298	0.307
service5	0.000	0.050	0.995	-0.005	0.061	0.940	-0.052	0.296	0.861
business1	0.007	0.050	0.890	-0.021	0.061	0.734	-0.304	0.320	0.341
business2	-0.021	0.049	0.667	-0.019	0.062	0.762	0.043	0.320	0.894
business3	-0.015	0.050	0.771	-0.018	0.061	0.771	-0.316	0.335	0.345
business4	-0.036	0.049	0.463	-0.055	0.061	0.360	0.491	0.327	0.133
business5	0.007	0.050	0.885	0.002	0.061	0.980	-0.802	0.351	0.022
AIC	***3759.014***			***3686.503***			***3420.813***		
Log Likelihood	***-1851.507 (df=28)***			***-1787.251 (df=56)***			***-1276.407 (df=434)***		
McFadden's R^2									
Num. obs.	***7824***			***7824***			***7824***		

Note: Colored cells correspond to p-values<0.05.

While all three models gave similar coefficient estimates for the aggregated data, the mixed logit models allow for extracting estimates of random effects on individual level and comparing them across different groups. We extracted such individual parameter estimates representing the utilities of high levels of each attribute and compared them across industries, countries, and industry-country combinations. Differences in mean parameter values were tested using a series of independent samples t-tests. The identified systematic differences between countries and industries at the 5% significance level are presented in Table 7.

4 Discussion

This section discusses the implications of the main results of this study. First, the perceived importance of supplier attributes is compared to the actual supplier choices made during the DCA stage. These results are then compared to the preceding literature in the supplier selection domain, followed by further country/industry analyses.

4.1 Perceived importance vs. actual choice

High levels of attributes with positive coefficients increase the supplier choice probability, while high levels of attributes with negative coefficients decrease it. According to the MXL model with correlated random effects (Table 6), high levels of new product availability, responsiveness to demand fluctuations, compliance with due date and product range all increase the probability of choosing a supplier. At the same time, delivery lead time, purchase price, internal quality control rejection rate, inelasticity of payment plans, risks associated with foreign trade, logistic and other costs, and lack of promotions all have a negative impact on choice probability.

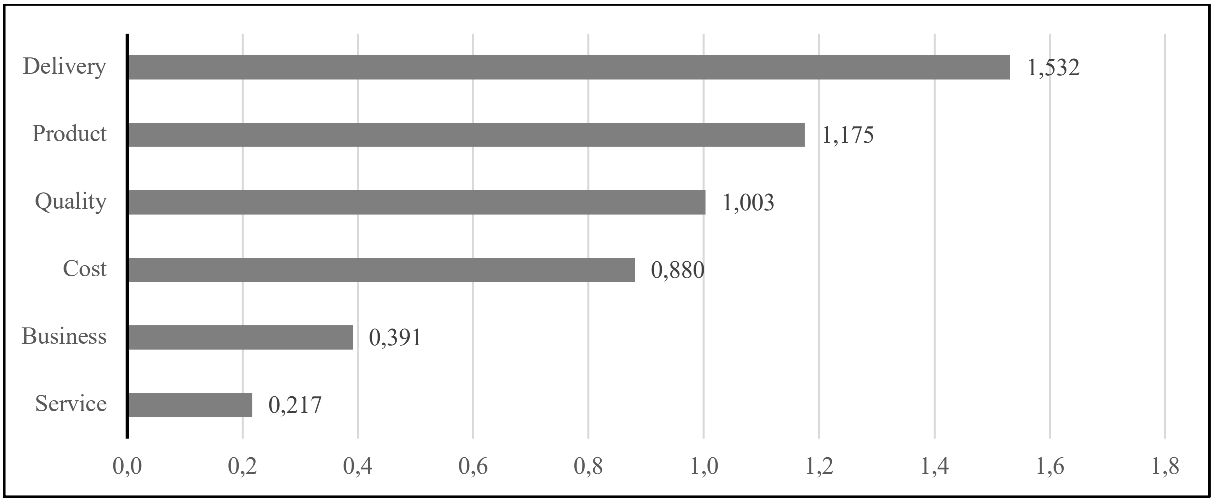
Table 7. Comparison of average parameter estimates across countries and industries

	Country		Industry		Industry				Country			
	India	Poland	Auto	FMCG	Auto		FMCG		India		Poland	
					Country		Country		Industry		Industry	
	Mean	Mean	Mean	Mean	India	Poland	India	Poland	Auto	FMCG	Auto	FMCG
opt1_2	1.32	0.05	0.79	0.85	1.58	-0.31	1.02	0.56	1.58	1.02	-0.31	0.56
quality1	-1.3	-1.8	-1.51	-1.49	-1.19	-1.95	-1.44	-1.58	-1.19	-1.44	-1.95	-1.58
quality2	0.69	0.47	0.71	0.47	0.85	0.53	0.51	0.4	0.85	0.51	0.53	0.4
cost1	-2.33	-0.56	-1.9	-1.26	-3	-0.37	-1.53	-0.82	-3	-1.53	-0.37	-0.82
cost2	-1.48	0.03	-0.97	-0.77	-1.8	0.2	-1.1	-0.21	-1.8	-1.1	0.2	-0.21
cost3	-1.28	-1.1	-1.4	-0.98	-1.38	-1.43	-1.18	-0.65	-1.38	-1.18	-1.43	-0.65
cost4	-1.7	0.45	-1.11	-0.51	-2.37	0.66	-0.9	0.15	-2.37	-0.9	0.66	0.15
cost5	0.16	0.24	0.44	-0.13	0.2	0.77	0.11	-0.51	0.2	0.11	0.77	-0.51
delivery1	2.82	2.18	2.82	2.24	3.35	2.09	2.21	2.31	3.35	2.21	2.09	2.31
delivery2	-2.33	-1.02	-1.61	-2.06	-2.23	-0.74	-2.45	-1.41	-2.23	-2.45	-0.74	-1.41
delivery3	0.42	-0.95	-0.04	-0.24	0.69	-1.05	0.09	-0.8	0.69	0.09	-1.05	-0.8
delivery4	0.1	-1.04	-0.11	-0.67	0.66	-1.19	-0.57	-0.83	0.66	-0.57	-1.19	-0.83
delivery5	2.45	2.99	2.72	2.6	2.39	3.18	2.52	2.72	2.39	2.52	3.18	2.72
product1	2.03	0.72	1.55	1.46	2.24	0.6	1.79	0.89	2.24	1.79	0.6	0.89
product2	3.07	3.01	2.83	3.33	2.76	2.92	3.44	3.14	2.76	3.44	2.92	3.14
product3	-0.32	2.24	0.86	0.51	-0.52	2.78	-0.08	1.49	-0.52	-0.08	2.78	1.49
product4	-0.18	-0.47	-0.28	-0.32	0.01	-0.69	-0.41	-0.16	0.01	-0.41	-0.69	-0.16
product5	-0.02	-0.78	-0.51	-0.09	-0.3	-0.8	0.31	-0.76	-0.3	0.31	-0.8	-0.76
service1	0.2	-0.38	-0.12	0.08	0.38	-0.81	0	0.21	0.38	0	-0.81	0.21
service2	-0.06	-0.73	-0.55	-0.03	-0.29	-0.92	0.22	-0.46	-0.29	0.22	-0.92	-0.46
service3	-0.11	-0.37	-0.49	0.14	-0.28	-0.78	0.09	0.22	-0.28	0.09	-0.78	0.22
service4	-0.7	-0.17	-0.52	-0.45	-0.96	0.09	-0.4	-0.53	-0.96	-0.4	0.09	-0.53
service5	0.02	-0.45	-0.16	-0.18	0.3	-0.82	-0.32	0.06	0.3	-0.32	-0.82	0.06
business1	-0.22	0	0.27	-0.64	0.1	0.5	-0.61	-0.71	0.1	-0.61	0.5	-0.71
business2	0.22	0	0.34	-0.12	0.36	0.3	0.06	-0.42	0.36	0.06	0.3	-0.42
business3	-0.36	0.01	-0.3	-0.1	-0.78	0.36	0.13	-0.49	-0.78	0.13	0.36	-0.49
business4	0.67	-0.13	0.25	0.48	0.65	-0.32	0.69	0.14	0.65	0.69	-0.32	0.14
business5	-0.45	-0.67	-0.35	-0.77	-0.2	-0.56	-0.74	-0.82	-0.2	-0.74	-0.56	-0.82

Note: Colored cells contain significantly higher (at the 5% significance level) absolute values of parameter estimates according to pairwise comparisons of column means

In order to be able to discuss the results of Likert scale questions and the MXL regression in parallel, we regrouped the effects established in the MXL regression into the six main attribute categories. The average beta parameter estimates per attribute category are summarized in Figure 6. For example, the quality attribute shows the average results from internal quality control rejection rate and customer review ratings.Delivery attributes were on average the most important, followed by product, quality, and cost features, while business performance and service attributes had rather negligible effect.

Figure 6. Mean beta parameter estimates for each group of attributes



A quick comparison of Figure 6 with Table 4 reveals that although the range of the perceived importance of the six attribute categories was not extremely wide, there are noticeable differences between the part-worth utilities of attributes when it comes to actual decision-making. Delivery and product turn out to be the most significant attribute categories, while business and service seem to play a negligible role. A similar comparison can be made for every subset of respondents, which is discussed later in this paper.

4.2 Comparison with previous literature

The results of the Likert scale questions for the full dataset show that service, product and quality were described as the most important supplier attributes. Past research in supplier selection has concluded that decision-makers perceive the most important attributes to be quality, followed by delivery and cost (Verma & Pullman, 1998). Comparing Table 4 to the results of Verma & Pullman (1998), we can see that the perceived importance of quality and cost seems lower in our case. However, standard deviations are quite large in both works, which make it difficult to compare the rest of our attributes with Verma & Pullman (1998), since those were not directly measured in their study. Our delivery attribute category could be considered as a combination of the lead-time, on-time delivery and flexibility attributes in Verma & Pullman (1998). Service and business performance were not analyzed in that study at all.

Comparing the MXL regression results of our full dataset (Table 6) to the results of Verma & Plaschka (2009) reveals that some of their significant constructs (or construct equivalents) also appear in our model as significant attributes. For example, delivery performance (Verma & Plaschka, 2009) can be considered as a combination of the following significant sub-attributes: compliance with the due date and delivery lead time. Demand flexibility (Verma & Plaschka, 2009) corresponds to responsiveness to demand fluctuations in our study. Similarly, variety flexibility (Verma & Plaschka, 2009) can be related to the combination of significant product attributes (product range, new product availability).

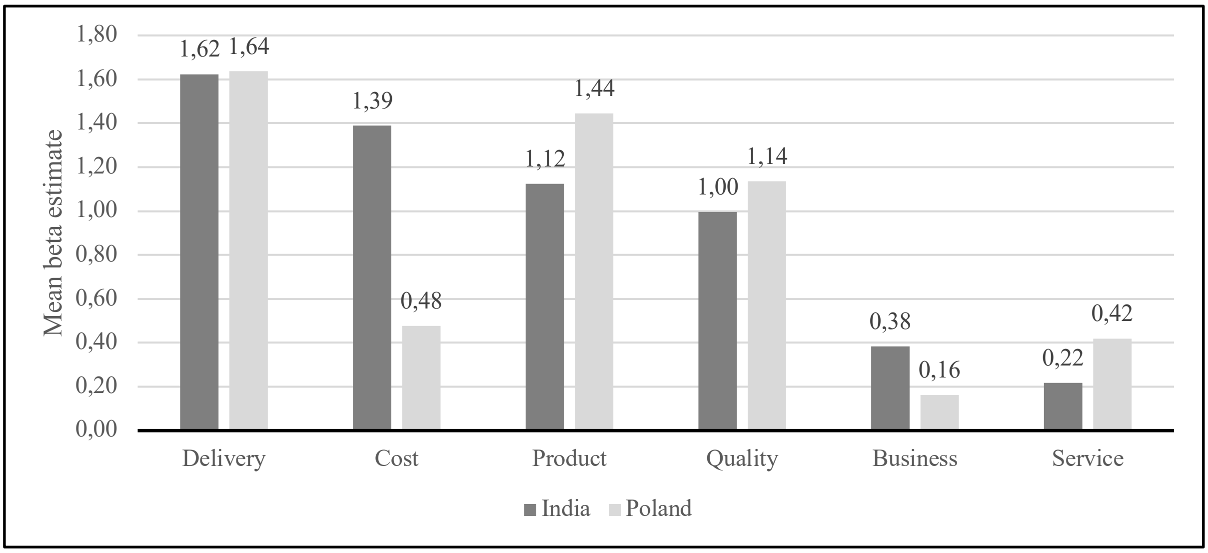
At the same time, the order of importance has changed over time. In our results, delivery and product categories include on average the most significant attributes. This change could be due to the supplier selection process evolving over the past decade. Globalization has caused suppliers to level out in terms of the most common attributes (e.g., cost and quality), which may have caused other factors to become more important in decision-making. Furthermore, when comparing the previous efforts with each other, it becomes even clearer that the significance of attributes has developed over time. Flexibility as an attribute was found to be non-significant in Verma & Pullman (1998), yet flexibility attributes were found to be significant in Verma & Plaschka (2009). However, in their experimental setup there was a lot of room for flexibility features since some of the other attributes (e.g., quality or product) were not taken into account or were leveled off at the acceptable threshold. Our results sample a wide range of attributes and still confirm that the flexibility attributes (payment plans and responsiveness to demand fluctuations) have very high part-worth utilities.

4.3 Further country/industry comparison

Cross-subset comparisons revealed that country differences appear to be more systematic than industry differences. In other words, although patterns of differences between India and Poland are rather similar for both industries, differences between the automotive and FMCG sectors are mostly country-specific. Compared to Polish respondents, representatives of both industries in India pay more attention to purchase price (cost1), logistics and other costs (cost2), lack of promotions (cost4), delivery lead time (delivery2) and product range (product1). In turn, executives in Poland are more sensitive to flexibility for change in delivery date (delivery3) and availability of add-on features (product3).

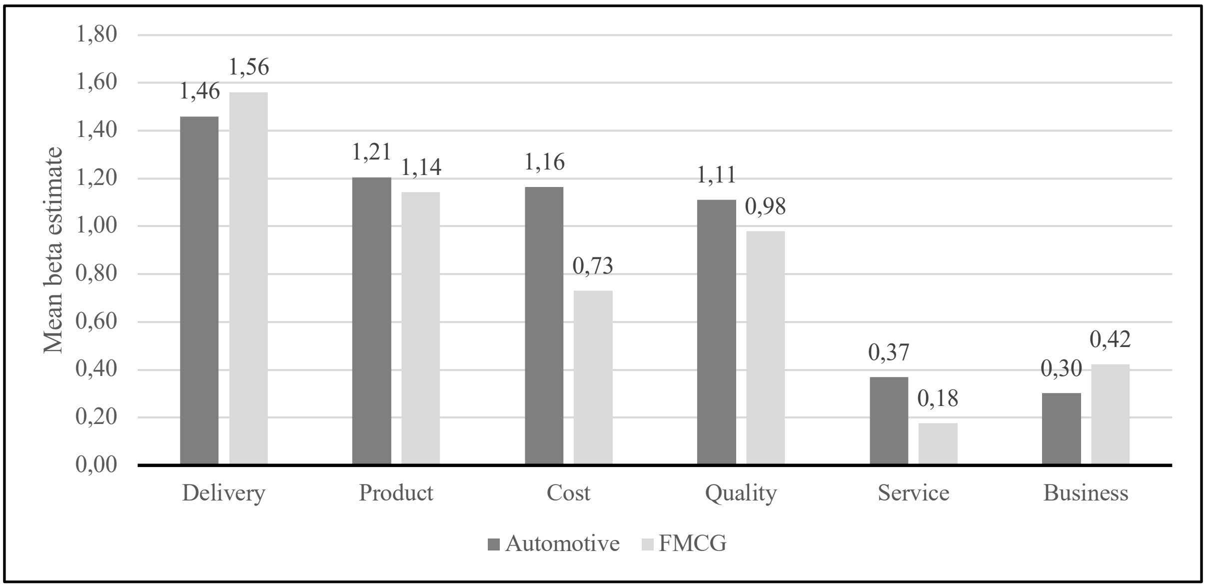
Averaging out the parameter estimates within groups of attributes and comparing them across countries and industries gives us several insights about the importance of various factors (Figures 7-9). First of all, the two most important attribute categories (delivery and product) are consistent across countries (Figure 7) and industries (Figure 8). A the same time, there are noticeable differences between countries in terms of cost and quality. The Polish subset of respondents is less cost-sensitive, giving more average weight to quality-related attributes. Another difference is that for Polish respondets service attributes, on average, tend to be more important than business attributes, while it is vice versa for the Indian subset.

Figure 7. Mean beta parameter estimates for each group of attributes: country comparison



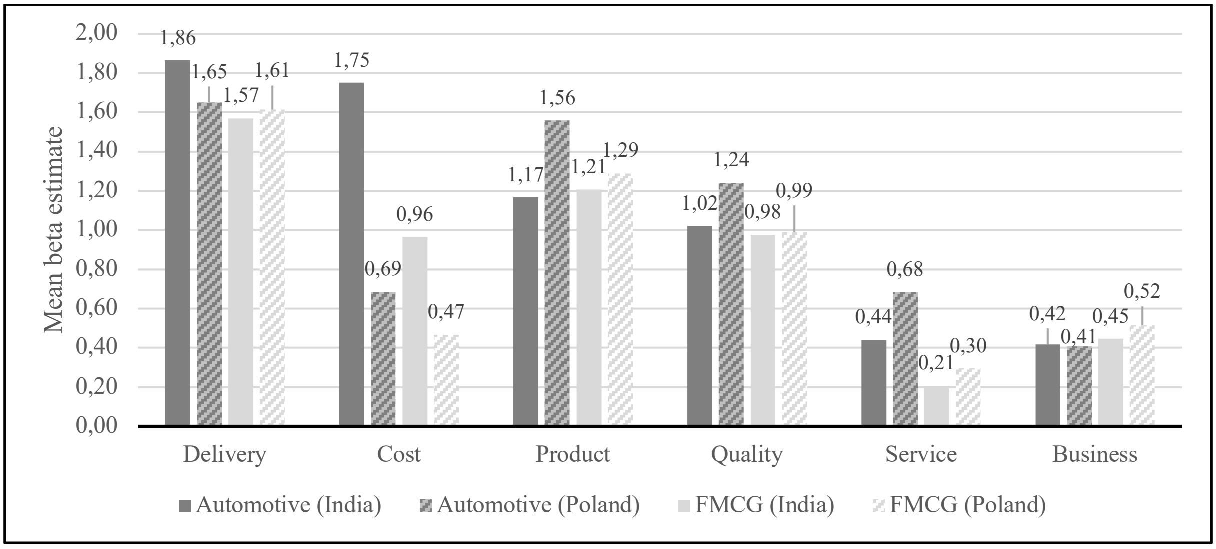
Additional differences can be found through industry comparison (Figure 8). While the representatives of the the automotive industry assign almost equal importance to cost and quality, their FMCG counterparts put more emphasis on quality-related factors. The role of service-related attributes is rather small for both industries, but it is especially negligible for FMCG. Further, the parameter estimates are more dominant in the automotive industry, with the exception of delivery and business performance categories.

Figure 8. Mean beta parameter estimates for each group of attributes: industry comparison



Finally, we calculated the mean parameter estimates for each of the four subsets to be able to compare them at once. The results of this cross-country cross-industry juxtaposition are presented in Figure 9. Perhaps the most relevant observation is the wide range of mean parameter estimates for the cost category. On average, cost-related attributes are given high importance in the automotive sector India, while their effect is rather low in the Polish FMCG industry. Except for the Indian automotive subset, delivery, product, and quality attributes are given the highest importance by the decision-makers. Consistently across all four country-industry combinations, business and service are the least relevant categories.

Figure 9. Mean beta parameter estimates for each group of attributes: comparison across industry-country combinations



5 Summary and conclusions

The existing literature in operations management argues that it is important for supply chain-related managerial decisions to be in line with the corporate strategy of a firm. This research was aimed at addressing one specific operations management aspect: the supplier selection process. The role of supplier selection has grown significantly over the past few decades as companies in different industries have started adopting different concepts of extended enterprise.

Our study was designed to understand how corporate executives tradeoff between multiple supplier attributes grouped into six main categories: quality, cost, delivery, product, service, and business performance. In order to compare our results with previous studies in this domain, we designed a two-stage process consisting of Likert scale questions and a discrete choice experiment. Our results show that, although there are no large differences in the perceived importance of various attributes suppliers are, in reality, chosen mostly based on their product and delivery performance. Quality and cost play a relatively smaller role for most groups of respondents, while service and business performance are often ignored by decision-makers. Each of the six aforementioned attribute categories was broken down into multiple attributes. This revealed the specific aspects that played a significant role within each category. Delivery lead time, responsiveness to demand fluctuations, and compliance with due date were all significant within the delivery category, whereas new product availability and product range played an important role amongst product-related attributes.

These results show certain consistency with how previous research in this domain has developed over the years (Verma & Pullman, 1998; Verma & Plaschka, 2009). According to Verma & Pullman (1998), flexibility attributes were rather insignificant, while Verma & Plaschka (2009) found a growing importance of flexibility, which was confirmed by our research. It is important to note that since the three studies (including our work) are all approximately a decade apart, the results have been subject to the changing world economy. Phenomena like globalization may have caused common attributes such as cost and quality to level out amongst different suppliers, increasing the role of other factors. Furthermore, modern concepts such as agile development are implemented by a multitude of players in many industries, which explains the shifting emphasis towards flexibility.

Furthermore, our research reveals some interesting differences from past studies in the supplier selection domain. To the best of our knowledge, this was the first attempt to conduct cross-industry and cross-country comparisons of the supplier selection process. Our dataset was compiled from responses from corporate executives working in the fast-moving consumer goods and automotive industries in Poland and India. Perhaps the most interesting finding of the discrete choice experiment is that there was more consistency across countries within the same industry than vice versa. In the FMCG industry, respondents from both countries attached the highest weights to product, quality, and delivery, respectively. Product and delivery were also in the top three attributes for the representatives of automotive OEMs in both countries.

5.1 Directions for future research

This study is not without its limitations. This is merely a first attempt to analyze the supplier selection process based on an advanced list of attributes by comparing two different industries across different geographical locations. Follow-up studies could fill some of the gaps that this effort has still left open. For example, only two levels were considered for each attribute when comparing supplier profiles: better or worse than the other alternative in a given choice task. This was done to prevent possible overcomplications of the analysis for the large number of sub-attributes. In future work, it would be interesting to either focus on a specific category of detailed attributes with more levels per attribute or conduct a very large study with a large number of attributes with customized levels. In addition, future work could expand on the number of industries or the number of countries.

We would advise choosing either of the two approaches to not contaminate the effect of industrial differences with the influence of the geographical and/or cultural factor. To further explore the geographical and/or cultural differences in supplier selection could prove insightful, where one industry might be examined across a variety of countries. Comparing several Central and Eastern European countries would be particularly interesting, given the lack of research for those geographies. In a similar fashion, one could choose a specific country and compare multiple industries within that country. Finally, this work leaves some open questions in the comparative analysis of attributes. As mentioned earlier in the final paragraph of the industry comparison section, there are some influences of attributes that are not fully explained. In-depth field work with industry experts would be needed to fully understand how executives interpret those attributes, and further cross-industry analysis could be conducted to explain the differences.

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Appendix 1

Table 8. Summary of the sample demographics

				Count	Column N %
Industry	**Automotive**			91	55.8%
	FMCG			72	44.2%
Country	**India**			98	60.1%
	Poland			65	39.9%
Age	**18 – 29**			6	3.7%
	30 – 44			97	59.5%
	45 – 59			55	33.7%
	60+			5	3.1%
Gender	**Female**			30	18.4%
	Male			133	81.6%
Industry	**Automotive**	**Age**	**18 - 29**	3	3.3%
			30 - 44	48	52.7%
			45 - 59	38	41.8%
			60+	2	2.2%
		Gender	**Female**	13	14.3%
			Male	78	85.7%
	FMCG	**Age**	**18 - 29**	3	4.2%
			30 - 44	49	68.1%
			45 - 59	17	23.6%
			60+	3	4.2%
		Gender	**Female**	17	23.6%
			Male	55	76.4%
Country	**India**	**Age**	**18 - 29**	2	2.0%
			30 - 44	51	52.0%
			45 - 59	42	42.9%
			60+	3	3.1%
		Gender	**Female**	13	13.3%
			Male	85	86.7%
	Poland	**Age**	**18 - 29**	4	6.2%
			30 - 44	46	70.8%
			45 - 59	13	20.0%
			60+	2	3.1%
		Gender	**Female**	17	26.2%
			Male	48	73.8%

Appendix 2

Three nested models were considered: 1) a model with no random effects, 2) a model with random but uncorrelated effects and 3) a model with random and correlated effects. Each was compared using likelihood ratio tests to determine the presence of random coefficients and to identify the correlation between them. Table 9 presents the results of two likelihood-ratio tests that favour the mixed logit model with correlated random effects. The hypothesis of no correlated random parameters was tested by comparing model 3 to model 1,and the null hypothesis was strongly rejected ($p<0.001$). The second test is a test of no correlation among random parameters when the existence of random parameters is maintained. The hypothesis of no correlation was strongly rejected as well ($p<0.001$). These results indicate that the mixed logit model with correlated random effects should be preferred.

Table 9. Results of Log-likelihood tests for model comparison

Compared models	Chi-square	DF	P-value
Model 1 vs. Model 3	1150.2	406	<0.001
Model 2 vs. Model 3	1021.7	378	<0.001

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