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# ENTREPRENEURS' PREFERENCES TOWARDS ONLINE MARKET RESEARCH PACKAGES: A DISCRETE CHOICE ANALYSIS

Ognjen NIKOLIĆ

*Laboratory for Operations Research "Dr Jovan Petrić" at Faculty of Organizational Sciences, University of Belgrade*
*ognjen.nikolic@fon.bg.ac.rs*

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**Abstract**: Startups have become a buzzword in the last couple of years, and entrepreneurship became career path for a number of people in the world. With all the advances in education and government subsidizing all over the world, still, statistics shows only a small percentage of successful startups. Studies have shown that the one the leading reasons for startup failure is the misreading of market's needs. The aim of this paper is to determine the approach to market research, knowledge of tools and methods, and preferences towards online market research tools of entrepreneurs by using Discrete Choice Analysis. The research gathered 187 valid responses from a panel of participants working on developing new products and business, using an online survey tool. In the paper it is shown that the most important attributes for entrepreneurs are the price of the market research tool, followed by the level of details in the report generated, with more in-depth analysis regarding segmentation, simulations, and Marginal Willingness to Pay in the further chapters. The results of the research imply the need for a market research business model optimized for those starting a new business, focused primarily on detailed reporting and analysis, with the pricing model adjusted to the lack of resources entrepreneurs face at the start of their ventures, which would help them better understand the market-fit at the beginning and raise the statistic of successful startups.

**Keywords**: Discrete choice analysis, preference, entrepreneurs, market research, innovation.

**MSC:** 62K10, 91B08, 91B10, 91B16.

## 1. INTRODUCTION

Global economy is changing, large companies have been laying off a large number of people in the last two years (only the tech companies in the US have laid off more than 250.000 since 2022 [1]) and the people are in need of jobs. With the current job market situation in the world, a lot of the people have turned to starting business of their own, and some of the startup accelerators have seen an increase in the number of applications per sources [2]. In the last 30 years, a lot has been done in the education sector, improving the teaching about entrepreneurship, especially in the business schools, preparing the students both for working in the companies, as well as creating a separate courses for managing entrepreneurial business and innovation [3], [4], [5], [6]. But still, the reports show that only a very small number of startups survive and become successful [3].

Researchers have been working to find out why that statistic is so low, and a number of reasons have come up, but one of the main ones for failure has been misinterpretation and misreading of current market's needs [7]. If that is not detected early in the work of a startup, or if the team is not prepared to be agile and pivot quickly, it can create big financial and motivational problems for the team and their future work, especially since the budget for initial development is mostly consisted of team's own finances [8].

Amjad et al. point out significant difference between the approach to creating the product or service between traditional marketing of bigger organizations, and entrepreneurial marketing of SMEs. Larger organizations have much more resources to utilize so they can afford to do top-down approach, and start first with the formal market research, followed by segmentation, choosing target markets and then positioning, while SME first choose a target group, and then try to find out about their needs and demands, mostly through personal relations [3]. In the preliminary phase of this research, through interviews with entrepreneurs, startup founders and their mentors, similar was concluded – they have the need for market research but lack the resources to conduct it in the proper way. They noted that their usual ways were through interviews with smaller number of representatives of the target group or conducting online surveys using free tools and their own network to spread the questionnaire and try to get responses. One of the biggest problems that they noted was finding the right incentive for somebody to be a part of their research, especially on a tight budget. If they wanted to use platforms that offer panels of respondents, they would have to pay between 300-12000€ per research, depending on the sample, number of filters, accuracy, and other factors.

The importance of market-driven entrepreneurship is especially described in [9] where the authors reviewed literature and pointed out that those entrepreneurs who are driven by perceived gaps in the market and who provide unique offerings according to them are those that create new values for the market, opposing those who start businesses solely as form of making a living. Not only is that important for the long-term survival of the startup, but also it has been proven that the investors highly regard the existence of high value addition of the product/service to the customers when deciding on their investments. Block et al. have researched the importance of several attributes for investors when considering investments using Conjoint analysis, and the value-added has come up as the second most important attribute to them [10].

Ali et al. in [9] also note two different point of views on the definition of entrepreneur citing McMullen and Sheperd [11] "To be an entrepreneur… is to act on the possibility that one has identified and opportunity worth pursuing" as well Schumpeter's [12] definition that states that the entrepreneur is an innovator, producing change that creates new needs in consumers. In the paper, it is also noted that entrepreneurship can also be expressed within organizations as well, not only in startups, which is the reason why this research also encompasses the responses from various respondents working in larger organizations, working directly on creating the products or in R&D departments.

Lean Startup Method (LSM) has been highly praised due to its nature to segmentation and iterative approach to business planning, especially with its focus on smaller iterations with immediate testing [13]. De Cock et al., have researched its impact on successfulness of the startups, with focus on the market knowledge of the startup founders. They've concluded that using LSM is insufficient for the success of the new business, without previous market knowledge. In the paper it is discussed that previous market knowledge helps with better interpretation of the test results and market information, helping them to create better problem-solution fit [14].

Today, with the rise of social media and strong digital tools for customer data, it feels like the customer insights are right there on the edge of the fingertips, and that should make it easier for entrepreneurs. But Cluley et al. discuss just how that might be misleading and how to properly use the data available through those channels, researchers need to adapt and learn more about the nature of the information technologies, as well as the researcher and the business owner need to be working closer together in order to design the research as best as possible. They cite reports claiming that being over-dependent on social media for market insights might create a downturn for the business if the people assigned to it lack technical skills and if the organization is not supporting it properly. They claim that market researcher of the future needs to play both the role of *social scientist*, meaning that they collect, analyze and report continuously, as well as the role of the *storyteller* (strategic consultant) and work with the business owners, engaging them in the research process in order to help them bring their consumers from findings to life [15]. Through the preliminary process of this research, it was seen that entrepreneurs want to incorporate data into their business and understand the importance of it, but do not have a strategic plan for it.

As mentioned, misunderstanding of market's needs and miscreating a product-market fit is one of the most common cases of startup failure. This research tries to find out how do entrepreneurs perceive market research, their level of knowledge, their main needs and their desired price range for a platform that would help them out with market research, with the goal of understanding their preferences when it comes to market research opportunities. The main research questions are:

- How confident entrepreneurs are about their knowledge of market research?
- Which methods and tools do they use now and plan to use in the future?
- How much are they willing to pay for an online questionnaire that would be filled out by their desired target?
- What are respondents' preferences towards key characteristics of the platform for online market research?

For those needs, a combination of interviews, simple questionnaire and a survey using Discrete Choice Analysis (DCA) was chosen. DCA or otherwise called Choice-Based Conjoint analysis, was chosen, as it is a method for measuring the unconscious preferences towards certain attributes when choosing between similar products. Its power lies in putting the respondents in the conflicted position where they must choose between several similar alternatives, differing in the levels of the same attributes. After a number of those choice tasks, their individual preferences can be determined. It gives a better understanding of their preferences, than just questioning the importance of each attribute on a linear scale, because their real preferences come up when they have to choose in those conflicted choice tasks. DCA has been used in a different areas of research, such as medicine [16], travel industry [17], online buyers decisions [18], agriculture [19] with more detailed numbers of its presence in the number of papers published for period of 1998-2017 on WoS given in [20]. In [20] it was shown that business economics is the category where DCA is used the most with around 39.5% of the published papers belonging to that category, followed by engineering and health care. In the literature review phase, no papers dealing with the similar problem of this research have been found, especially no ones using the DCA to find the preferences of entrepreneurs on the subject of market research tools. This paper explores that gap and expands the literature on the subject, with the goal of revealing true preferences of entrepreneurs regarding the online market research tools, suggesting further recommendations for improving development of startups with the aim of helping them reach their market-fit, and raise the statistic of successful startups, which will positively impact the economy.

As stated before, through literature review and interviews with the entrepreneurs it was concluded that they need better market research but lack funding or expertise to conduct it properly. In this paper their current knowledge about market research methodologies and preferences towards online market research tools will be presented, as well as the segmentation of the results. In the first chapter, research design will be explained with the focus on the DCA method, and how the experiment was set up using it. Results will be presented in the third chapter, describing sample characteristics, aggregated preferences, marginal willingness to pay for certain features and differences between segments. Finally, in the last section, discussion and conclusion with future research will be presented.

## 2. RESEARCH DESIGN

### 2.1. Discrete Choice Analysis

Discrete Choice Analysis is an analytical method for measuring the importance of certain attributes and their levels of a given object (e.g., product or a service) on the subjects of the research (respondents), grounded in random utility theory. Main contribution of DCA is that it puts attributes and their levels in conflict position, so that it can be precisely measured which attribute and which level is more preferred by the respondents of the research [21].

In DCA experiments respondents are shown different alternatives of the object of research, consisting of the same attributes, that can be qualitative or quantitative, but differing in levels of those attributes. In any of the cases when they are presented with those alternatives, respondents are expected to choose rationally between them, meaning that they choose the one that maximizes total value for them. Main output of DCA, after all respondents choose their preferred alternatives in a given number of simulations are utility scores, that measure to which extent each attribute, and each level of those attributes impact choices for each respondent. That gives the opportunity not only to analyze the aggregated results, but also to do more in-depth analysis, clustering and run different simulations to find the best scenario [21].

DCA is derived from random utility theory and specifies the probability that the respondent chooses a particular alternative, expressed as a function of observed variables that relate both to the alternative and to the respondent. In the general model, assume that $I$ respondents choose from the set of $J$ mutually exclusive alternatives, where each respondent receives some utility from each of the alternatives, Each respondent is expected to behave rationally by choosing the alternative from the given choice task that maximizes their utility, meaning that an individual $i$ $(i = 1, \dots, I)$, would choose alternative $j$ $(j =$

$1, \ldots, J)$ if and only if the utility of that alternative $U_{ij}$ is greater than or equal to the utility of all other alternatives, with utility given by [21]:

$$U_{ij} = V_{ij} + \varepsilon_{ij}, \tag{1}$$

where $\varepsilon_{ij}$ is a stochastic component and $V_{ij}$ is a deterministic component, that answers to the goal of a choice model to identify the attributes that affect the utility individuals and estimate their importance values. $V_{ij}$ is specified by a functional form, that is usually a linear additive model [21]:

$$V_{ij} = \sum_{k=1}^{K} \sum_{l=1}^{L_k} \beta_{ikl} x_{jkl}, \quad i = 1, \ldots, I, \quad j = 1, \ldots, J, \tag{2}$$

where $K$ is the number of attributes; $L_k$ is the number of levels of attribute $k$, $\beta_{ikl}$ is respondent $i$'s utility with respect to level $l$ of attribute $k$ (so called part-worth utility) and $x_{ikl}$ is binary variable that equals 1 if alternative $j$ has attribute $k$ at level $l$, otherwise it equals 0. Accordingly, the probability that the alternative $j$ will be chosen by an individual $i$ from a set of four mutually exclusive alternatives is given by [22]:

$$P_{ij} = \frac{e^{U_{ij}}}{\sum_{j=1}^{4} e^{U_{ij}}} \tag{3}$$

Markov Chain Monte Carlo Hierarchical Bayes (MCMCHB) was used to estimate the model parameters (part-worths). This way, part-worth utilities are estimated per individual, and not market as a whole, which makes it possible to calculate relative importance of attributes on different groups of individuals as well. Relative importance scores are calculated by taking the utility range for each attribute separately and then dividing it by the sum of the utility ranges for all the attributes [22].

### 2.2. Attribute and Levels

The first step in DCA, and the most important one, is to determine the key attributes that can influence the choice of the respondents. In our study, the object of research was a subscription package for an online-market research platform, with its own panel of respondents, designed for early-stage startups, so the attributes and their levels were chosen based on the literature review, and on the interviews conducted with startup founders and startup mentors, where they expressed their needs and expectations from market research in general, as well as benefits that they see in early market research for a startup. The final attributes and levels with brief descriptions are given in **Table 1**.

**Table 1:** Attributes and levels in the DCA

| Attribute | Levels | Description |
|---|---|---|
| Price | 150 €, 300 €, 400 €, 500 € | Price for an yearly subscription package |
| Number of surveys | 1, 3, 5 | Number of surveys that can be run in a year |
| Number of questions | 10, 30, 50 | Number of questions that can posed in a survey |
| Confidence interval | 90%, 95% | Confidence interval for the results of the survey |
| Hours of consultations with an expert | 0, 2, 4, 6 | Hours of consultations including help for creating the survey and analyzing the results |
| Days for getting the report | 3, 5, 7 | How soon would they like to get the answers, since launching a survey |
| Level of details in a report | No report – just raw data*, Basic**, Detailed*** | *Only excel file with data<br>**+Distribution of answers per question<br>***+Key correlations and segmentations |

To ensure that all the alternatives presented to the respondents are realistic, rule was made that lowest level of price attribute (150 €) cannot be combined with highest level of the attribute Number of surveys (5), as well as the highest level of the attribute Number of questions per survey (50), since the cost of the panel in that case would be too high, and no platform would give out that kind of option.

### 2.3. Experimental Design

Randomized block design was used to generate different sets of choice tasks, consisting of alternatives combined from the different levels of the attributes in **Table 1**. A total of 10 different blocks of 8 tasks with 4 alternatives were created. Those alternatives represented possible subscription packages for an online market research platform, with its own survey creating tool and the panel of respondents, that would ensure that the user creates the survey easily, gets it filled out by their desired target group, and in the end gets the report. One example of the choice task can be seen in **Error! Reference source not found.**.

**Figure 1:** Example of a choice task

| | Package A | Package B | Package C | Package D |
|---|---|---|---|---|
| *Price* | 150 € | 300 € | 500 € | 400 € |
| *Surveys* | 3 | 1 | 1 | 3 |
| *Questions* | 30 | 30 | 50 | 10 |
| *Accuracy* | 90% (standard) | 90% (standard) | 90% (standard) | 95% |
| *Quickness of results* | 5 workdays | 5 workdays | 7 workdays | 3 workdays |
| *Consultations* | Total 2 hours | Don't exist | Total 2 hours | Total 4 hours |
| *Report* | Basic* | Basic* | Detailed** | Detailed** |

After each choice task respondents had the option to opt out if they would really use that type of alternative or not. And with each choice they made, and each opting out, the algorithm would give them a harder choice task, putting to conflict those attributes that it found were most preferred by the respondent in the previous set, in order to truly define what the most important attribute and level for the given respondent was.

### 2.4. Implementation

For creation and conducting of the survey online platform Conjontly was used [23]. It has been shown that online surveys are more suitable for respondents, as well as for result analysis, when using DCA methodology [22]. Since the main target group were entrepreneurs, freelancers and product managers, the survey was shared through startup newsletters, shared in entrepreneurial groups on social media, as well as through posts on social media, but targeting entrepreneurs, product managers and UX designers. Also, to incorporate future entrepreneurs survey was shared among students of management and IT who are in their last year of study, and who desire to start a business of their own.

In order to do more in-depth analysis, the questionnaire consisted of four parts: (1) questions regarding demographic of the respondent, (2) questions regarding their current knowledge and self-rating on market research methodologies, (3) questions regarding optimal pricing for the online market research platform (using Van Westendorp methodology) and (4) 8 choice tasks.

## 3. RESULTS

### 3.1. Sample characteristics

There were 187 valid answers in the survey. Out of them 34.8% of respondents declared themselves as entrepreneurs, 33.7% as product managers/designers, 16.9% as UI/UX designers, 7.9% as members of the research and development teams, 12.4% as researchers. Additionally, 37.5% work in startups, scaleups and middle companies, 14.4% as freelancers, and 52.9% were students at the time. It is interesting to note that 73% of all the respondents work in the IT industry.

The self-assessment of the knowledge of market research was a good first indicator of the respondents' current usage and self-confidence when it comes to market research methodologies. Only 19.8% respondents rated their knowledge of market research techniques with grades 4 or 5, while the rest (80.2%) rated their knowledge 3 or below, on a scale of 1 to 5. The result was a mean value of 2.8 with standard deviation of 0.9. When asked for some of the more known methodologies, only 15.8% selected that they have heard about Conjoint analysis, 7.7% for Van Westendorp Price Sensitivity Analysis, and 3.3% selected that they have heard about Monadic testing. Additionally, it can be noted that the entrepreneurs are more likely to use secondary research, and qualitative methods, rather than quantitative ones, which can be seen in Figure 2, where the percentage of respondents that have heard about it (left pillar), and the percentage of respondents who plan to use it in the future (right pillar) are shown.

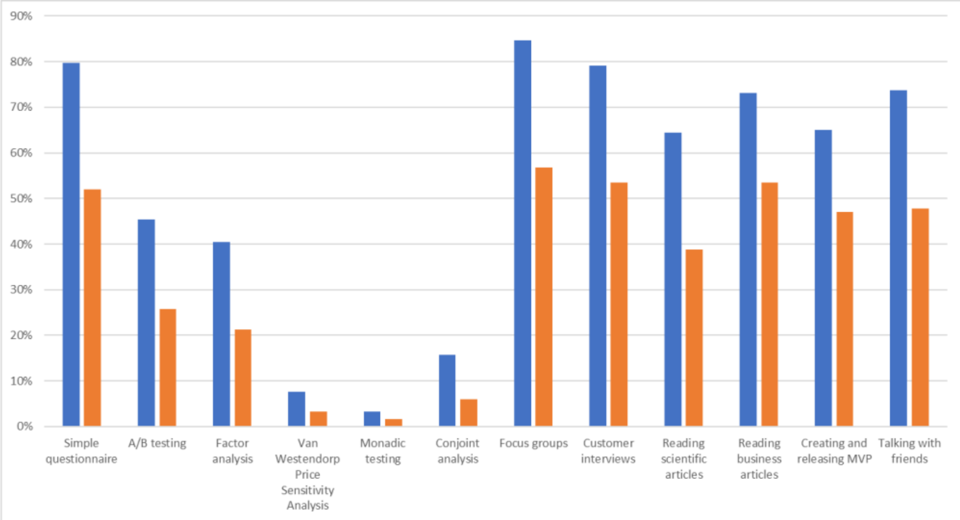


**Figure 2:** Self-assessment of market research methods

### 3.2. Aggregated preferences

McFadden’s pseudo-$R^2$ equals 59.3% which implies medium goodness of fit. The utility parameters were estimated both for each respondent in the sample (individual preferences), and for the total sample (aggregated preferences). The aggregated part-worth utilities for each can be seen in **Table 2**, and the relative importance of the attributes in **Figure 3**.

Although the price as an attribute has the highest relative importance, *detailed* level of the *report* attribute has the highest relative part-worth utility, followed by the *150 €* level of the price. Additionally, the highest price (*500 €*) has the most negative relative part-worth utility, followed closely by the lowest level of details (*no report, just raw data*). All that accounts for why the price and the detailed report are the attributes with the highest relative importance, combining for 53.1%.

Consultations have proven to be the third most important attribute, but it is interesting that *non-existence of the consultations* is far more influential when making a decision, ranked third by its negative relative part-worth utility across all levels of the attributes, than the difference in number of hours, which can be seen especially in the close relative part-worth utilities of the level *4 hours*, and level *6 hours*.

**Table 2:** Averaged preferences of levels

| Attribute | Level | Averaged preferences | Lower bound | Upper bound |
|---|---|---|---|---|
| | | | of 90% confidence interval | |
| Price | 150 € | 0.132 | 0.12 | 0.143 |
| | 300 € | 0.085 | 0.078 | 0.092 |
| | 400 € | -0.057 | -0.065 | -0.049 |
| | 500 € | -0.16 | -0.17 | -0.148 |
| Surveys | 1 | -0.083 | -0.09 | -0.076 |
| | 3 | 0.027 | 0.023 | 0.03 |
| | 5 | 0.056 | 0.049 | 0.063 |
| Questions | 10 | -0.031 | -0.036 | -0.026 |
| | 30 | 0.009 | 0.004 | 0.015 |
| | 50 | 0.021 | 0.015 | 0.027 |
| Accuracy | 90% (standard) | -0.032 | -0.036 | -0.028 |
| | 95% | 0.032 | 0.028 | 0.036 |
| Quickness of results | 3 workdays | 0.003 | 0 | 0.006 |
| | 5 workdays | 0.008 | 0.004 | 0.012 |
| | 7 workdays | -0.012 | -0.016 | -0.007 |
| Consultations | Don't exist | -0.095 | -0.099 | -0.091 |
| | Total 2 hours | 0.019 | 0.013 | 0.026 |
| | Total 4 hours | 0.036 | 0.029 | 0.042 |
| | Total 6 hours | 0.04 | 0.035 | 0.045 |
| Report | No report, just raw data | -0.156 | -0.165 | -0.146 |
| | Basic | 0.012 | 0.007 | 0.018 |
| | Detailed | 0.143 | 0.132 | 0.154 |

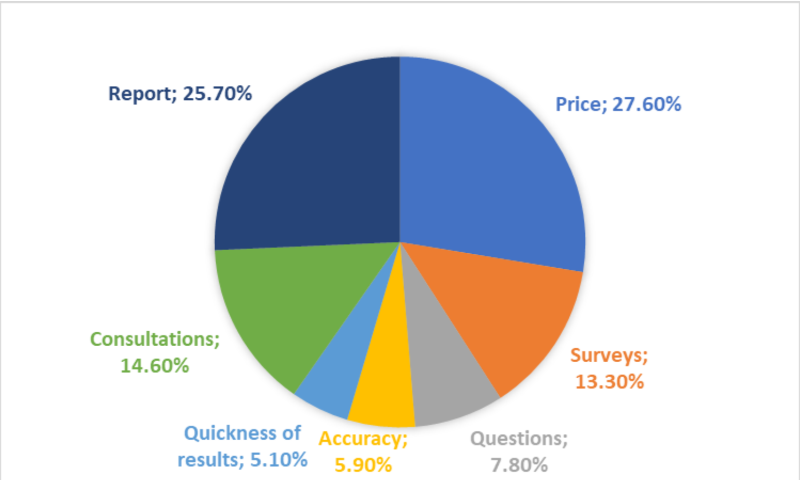


**Figure 3:** Relative aggregated preferences for attributes

### 3.3. Marginal willingness to pay

One of the advantages of the DCA, combined with the price attribute is calculating the marginal willingness to pay (MWTP) to get another level of an attribute, with all other levels of other attributes staying on their existing level, which can also reflect the importance of the level of the attribute [24]. For that, the baseline alternative is chosen, which for this paper was the one combined of the lowest level of the attributes. MWTP can be assessed by the respondent-level part-worth calculated by Hierarchical Bayes:

$$MWTP_{ik} = \frac{\Delta P}{\Delta\beta_{i,price}} \times \Delta\beta_{ik} \tag{4}$$

where $\Delta P$ is a range in price levels, $\beta_{i,price}$ is the range in part-worth utilities attached to the price attribute by respondent $i$, and $\Delta\beta_{ik}$ is the range in utility attributable to attribute $k$ for the respondent $i$. After this is done for all levels of all attributes, MWTP can be then determined as the median of the respondents' willingness to pay for all attribute levels [24].

The result of the MWTP analysis is given in the **Figure 4**, where it can be seen that the respondents would be ready to pay 313.63€ more to have the *detailed report*, which is directly correlated to the relative part-worth utility of that level as well as the high relative part-worth utility of the price of *300€*. Also, the *basic level of the report*, *6 hours of consultation* and *5 surveys* have a high MWTP price as well. Small difference in the relative part-worth utility of the number of hours of consultation can also be seen in the difference in MWTP for different levels of that attribute.

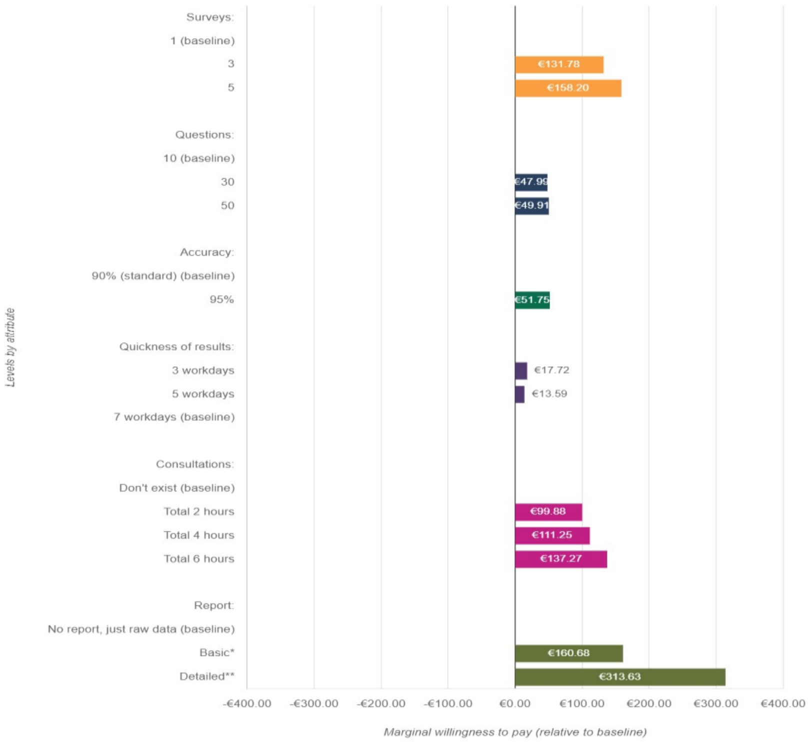


**Figure 4:** Marginal Willingness to Pay for each level

### 3.4. Simulations

Simulation 1

Interesting results come up when doing simulations on the Conjointly platform. In the first simulation two products, that are leveled the same on all attributes except for the price, where one is on the level of 150€, and the other one on 300€, and for the attribute report, one is *No report*, while the other is on the *Detailed report* level, were set up. Simulation showed that the preference share would go in favor of the more expensive product, with the detailed reporting, winning 71.9% shares. In order for the 50/50 split to occur, the price of the second product would have to go to exactly 479€.

Simulation 2

In simulation 2 three subscription packages were created, simulating the real possible packages of a such online-market research platform. Their levels are given in **Table 3**.

**Table 3:** Subscription packages for Simulation 2

| | Package 1 | Package 2 | Package 3 |
|---|---|---|---|
| **Price** | 150 € | 300 € | 500 € |
| **Surveys** | 3 | 5 | 5 |
| **Questions** | 10 | 10 | 30 |
| **Accuracy** | 90% | 90% | 95% |
| **Quickness of results** | 5 workdays | 5 workdays | 5 workdays |
| **Consultations** | 2 hours | 2 hours | 4 hours |
| **Report** | Basic | Detailed | Detailed |

The results of the simulations showed an almost equal distribution of preference shares between these three packages. In that scenario package one would have 35.1%, package two 34.4% and package 3 30.1% preference shares, which is quite interesting to see, since the price of 500€ had the most negative part-worth utility on the aggregated set. This goes to show that 30.1% respondents preferred this combination in the alternative more than the lower price.

### 3.5. Segmentation

As for more in-depth analysis, the first thing was to look if there is a difference in preference levels between different segments of the respondents. Analyzed segments were male, female and entrepreneurs.

Male and female segments

Difference can be seen between male and female participants in the levels of main attributes. There is a 2.9% difference in relative part-worth utility when it comes to preferring the lowest level of the price attribute. Male respondents have shown stronger preference toward that level with 14.9% relative part-worth utility, whereas female respondents have a lower preference with 12%. Regarding the second most preferred level – detailed level of the attribute report, it is more preferred by female respondents with 15.6% of relative part-worth utility, and is less preferred by male respondents with 12.6%, creating a difference of 3% between these two segments. Also, the same can be seen with negative part-worth utility of the lowest level of that attribute, where it has -13.9% importance for the male respondents, and -16.8% for the female respondents. This affects the difference in the relative importance of the attributes, with the biggest difference of 5% in preferring the attribute report (male respondents 22.8%, female 27.8%), following by a difference of 2.6% for the surveys (male respondents 14.8%, female 12.2%) and 2.2% for the price attribute (male respondents 28.9%, female 26.6%). All the data can be seen in **Table 4**.

**Table 4:** Aggregated preferences for male and female segments

| Attribute | Male | Female | Level | Male | Female | All |
|---|---|---|---|---|---|---|
| Price | 28.9% | 26.6% | 150 € | 14.9% | 12.0% | 13.2% |
| | | | 300 € | 7.8% | 9.0% | 8.5% |
| | | | 400 € | -6.4% | -5.2% | -5.7% |
| | | | 500 € | -16.2% | -15.8% | -16.0% |
| Surveys | 14.8% | 12.2% | 1 | -9.2% | -7.6% | -8.3% |
| | | | 3 | 2.5% | 2.7% | 2.7% |
| | | | 5 | 6.6% | 4.9% | 5.6% |
| Questions | 8.0% | 7.7% | 10 | -3.7% | -2.6% | -3.1% |
| | | | 30 | 0.7% | 1.1% | 0.9% |
| | | | 50 | 3.0% | 1.5% | 2.1% |
| Accuracy | 5.6% | 6.0% | 90% (standard) | -3.0% | -3.3% | -3.2% |
| | | | 95% | 3.0% | 3.3% | 3.2% |
| Quickness of results | 5.5% | 4.8% | 3 workdays | 0.3% | 0.4% | 0.3% |
| | | | 5 workdays | 0.6% | 1.0% | 0.8% |
| | | | 7 workdays | -0.8% | -1.4% | -1.2% |
| Consultations | 14.4% | 14.8% | Don't exist | -9.2% | -9.8% | -9.5% |
| | | | Total 2 hours | 2.6% | 1.4% | 1.9% |
| | | | Total 4 hours | 3.3% | 3.9% | 3.6% |
| | | | Total 6 hours | 3.3% | 4.5% | 4.0% |
| Report | 22.8% | 27.8% | No report, just raw data | -13.9% | -16.8% | -15.6% |
| | | | Basic* | 1.3% | 1.2% | 1.2% |
| | | | Detailed** | 12.6% | 15.6% | 14.3% |

Entrepreneur segment

Even though all the respondents fit into the category of entrepreneurs from the point of innovating and creating new products for the market, the segment of people who are actually working in the startups and creating startups of their own is quite important for this study, so this segment is to be analyzed independently. The main difference for this segment of respondents is seen in the price and report attributes. By far the most important attribute for the entrepreneurs is the price, with 30.2% relative importance, 2.6% more than when looking at all the respondents, and the report attribute falls from 25.7% to 22.6%, comparing to all respondents. The price of 150€ has the part-worth utility of 15.4%, while the negative utility of lowest level of report is -13.5%, both differentiating more than 2% from the general segment.

**Table 5:** Aggregated preferences for the Entrepreneur segment

| Attribute | Relative importance | Level | Entrepreneurs | All |
|---|---|---|---|---|
| Price | 30.2% | 150 € | 15.4% | 13.2% |
| | | 300 € | 8.2% | 8.5% |
| | | 400 € | -6.6% | -5.7% |
| | | 500 € | -17.1% | -16.0% |
| Surveys | 13.8% | 1 | -8.6% | -8.3% |
| | | 3 | 2.5% | 2.7% |
| | | 5 | 6.1% | 5.6% |
| Questions | 8.1% | 10 | -3.5% | -3.1% |
| | | 30 | 0.9% | 0.9% |
| | | 50 | 2.6% | 2.1% |
| Accuracy | 5.6% | 90% (standard) | -3.0% | -3.2% |
| | | 95% | 3.0% | 3.2% |
| Quickness of results | 5.5% | 3 workdays | 0.0% | 0.3% |
| | | 5 workdays | 0.8% | 0.8% |
| | | 7 workdays | -0.8% | -1.2% |
| Consultations | 14.3% | Don't exist | -9.2% | -9.5% |
| | | Total 2 hours | 2.6% | 1.9% |
| | | Total 4 hours | 3.3% | 3.6% |
| | | Total 6 hours | 3.4% | 4.0% |
| Report | 22.6% | No report, just raw data | -13.5% | -15.6% |
| | | Basic* | 0.4% | 1.2% |
| | | Detailed** | 13.1% | 14.3% |

This strongly affects the marginal willingness to pay, where entrepreneurs are willing to pay 212.85€ for the detailed level of report, which is around 100€ less than the average respondent. For basic level of the report, the difference amounts to 45€ less, and the big difference can be seen with the highest level for consultations where the average respondent would be willing to pay around 137€, the respondent from this segment would only be willing to pay 101.38€. The difference for MWTP for the levels of consultations is almost non-existent in this segment. For the level of 2 hours MWTP is 86.12€, for 4 hours is 97.25€, and as mentioned for 6 hours is 101.38€.

## 4. CONCLUSION

When looking at the data from the second set of questions regarding the respondents' knowledge and self-assessment about market research techniques it isn't somewhat surprising to see that the quality of the report and the consultations of the experts are listed high on their scale of importance. The thing that might be surprising is how little they "plan to invest" in a series of studies throughout one year, putting the lower price on the highest spot, with the negative part-worth utility for the prices over 400€, especially knowing that the one of the biggest reasons for startup failure is misinterpretation of market needs. Still, it is interesting to see that in the conflict of lower price and higher expertise, lower price wins by a small margin. The simulations showed that even so, the more expensive alternative (300€) would have a much larger preference share than the one priced at 150€, when the main difference is the level of details in the report. And when three packages are created with different prices and offerings aligning with those prices, the preference share would be almost equal, meaning that there are people on the market appraising higher quality of market research tool and the value it brings than the price it costs.

On the other hand, the results show that they value conducting more smaller surveys, than few bigger ones, rating the higher levels for number of surveys more important, far more than higher levels for the number of questions, in a year. That may create a problem for doing more in-depth analysis, and providing those highly detailed reports, when there are fewer things to analyze.

The results of the research show that entrepreneurs do feel the need to do proper market research, but lack knowledge to do it on their own, or finances to outsource it to an expert. This paper suggests finding a market research business model optimized for businesses in the beginning stages, with focus primarily on detailed reporting and analysis, and pricing model adjusted to the financial possibilities of startups at the start, with a goal of helping them find their market-fit, and raise their chances for success, developing a better startup ecosystem, and by that the economy. Also, the paper suggests continuation of integrating entrepreneurial education in the schools, and the government subsidized programs for early-stage startups, with the added focus on market research. With the recent literature review, results of the study, conclusions and suggestions presented, paper contributes to the literature and provides new insights into the topic of entrepreneurs and market research.

The research itself has its limitations. Panel of respondents was limited to Serbia, because of the easier access to respondents from the network and even then, collection of responses took almost two months. In the future, it would be interesting to compare the results with representatives of other countries, especially the ones where startup ecosystem is better developed, with higher number of successful startups. The research was also limited to the idea of an online market research tool promising valid representation and valid answers from a given panel, which may be suspicious to those who haven't come across similar tools or prefer the pen and paper style of surveying. And lastly, the success factor of respondents for their products, startups or mentorships hasn't been taken into consideration, which would have been interesting to explore and combine with their preferences towards market research practices.

Still, at the end, the question stays open – given that founders usually don't have investors at the beginning, but use their own money, would it be cheaper for them, or at least do they perceive it as cheaper, to test their ideas through several different surveys with the current prices and their knowledge of market research rather than spend months in development before finding that the idea is not a market-fit.

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## REFERENCES


[1] Crunchbase, "The Crunchbase Tech Layoffs Tracker," Crunchbase, 28 7 2023. [Online]. Available: https://news.crunchbase.com/startups/tech-layoffs/. [Accessed 2 8 2023].

[2] Wired, "Tech Layoffs Are Feeding a New Startup Surge," Wired, 22 2 2023. [Online]. Available: https://www.wired.com/story/tech-layoffs-are-feeding-a-new-startup-surge/. [Accessed 2023 8 2023].

[3] T. Amjad, S. H. B. A. Rani and S. B. Sa'atar, "Entrepreneurship development and pedagogical gaps in entrepreneurial marketing educatio," *The International Journal of Management Education,* vol. 18, no. 2, 2020.

[4] K. K. Longva, Ø. Strand and M. Pasquine, "Entrepreneurship education as an arena for career reflection: the shift of students' career preferences after a business planning course," *Education+ Training,* vol. 62, no. 7/8, pp. 877-896, 2020.

[5] A. Tittel and O. Terzidis, "Entrepreneurial competences revised: developing a consolidated and categorized list of entrepreneurial competences," *Entrepreneurship Education,* vol. 3, pp. 1-35, 2020.

[6] D. F. Kuratko, G. Fisher and D. B. Audretsch, "Unraveling the entrepreneurial mindset," *Economics,* vol. 57, pp. 1681-1691, 2021.

[7] R. Bednár and N. Tarišková, "Indicators of startup failure," *Industry 4.0,* vol. 2, no. 5, pp. 238-240, 2017.

[8] Digital Serbia Initiative, "Startup Scanner," 2022. [Online]. Available: https://www.preduzmi.rs/wp-content/uploads/2022/04/Startup_Skener_ENG.pdf.

[9] A. Ali, D. J. Kelley and J. Levie, "Market-driven entrepreneurship and institutions," *Journal of Business Research,* vol. 113, pp. 117-128, 2020.

[10] J. Block, C. Fisch, S. Vismara and R. Andres, "Private equity investment criteria: An experimental conjoint analysis of venture capital, business angels, and family offices," *Journal of corporate finance,* vol. 58, pp. 329-352, 2019.

[11] J. S. McMullen and D. A. Shepherd, "Entrepreneurial action and the role of uncertainty in the theory of the entrepreneur," *Academy of Management review,* vol. 31, no. 1, pp. 132-152, 2006.

[12] J. A. Schumpeter, The theory of economic development, Cambridge, MA: Harvard University PRess, 1934.

[13] M. Leatherbee and R. Katila, "The lean startup method: Early-stage teams and hypothesis-based probing of business ideas," *Startegic Entrepreneurship Journal,* vol. 14, no. 4, pp. 570-593, 2020.

[14] R. De Cock, J. Bruneel and A. Bobelyn, "Making the lean start-up method work: the role of prior market knowledge," *Journal of Small Business Management,* vol. 58, no. 5, pp. 975-1002, 2020.

[15] R. Cluley, W. Green and R. Owen, "The changing role of the marketing researcher in the age of digital technology: Practitioner perspectives on the digitization of marketing research," *International Journal of Market Research,* vol. 62, no. 1, pp. 27-42, 2020.

[16] Y. Wang, Z. Wang, Z. Wang, X. Li, X. Pang and S. Wang, "Application of discrete choice experiment in health care: a bibliometric analysis," *Frontiers in Public Health,* vol. 9, 2021.

[17] M. Vukić, M. Kuzmanović and M. Kostić Stanković, "Understanding the heterogeneity of Generation Y's preferences for travelling: A conjoint analysis approach," *International Journal of Tourism Research,* vol. 17, no. 5, pp. 482-491, 2015.

[18] B. Lu and S. Zhang, "A conjoint approach to understanding online buyers' decisions towards online marketplaces," *Journal of theoretical and applied electronic commerce research,* vol. 15, no. 3, pp. 69-83, 2020.

[19] T. Čop and M. Njavro, "Application of discrete choice experiment in agricultural risk management: a review," *Sustainability,* vol. 14, no. 17, 2022.

[20] M. Misuraca, G. Scepi and M. Spano, "A bibliometric study on the evolution of conjoint analysis in 1998-2017," *Statistica Applicata-Italian Journal of Applied Statistics,* vol. 1, pp. 9-27, 2020.

[21] M. Kuzmanović, D. Makajić-Nikolić and N. Nikolić, "Preference based portfolio for private investors: Discrete choice analysis approach," *Mathematics,* vol. 8, no. 1, 2019.

[22] M. Kuzmanović and M. Vukić, "Incorporating heterogeneity of travelers’ preferences into the overall hostel performance rating," *Decision Making: Applications in Management and Engineering,* vol. 4, no. 2, pp. 200-224, 2021.

[23] conjointly, "How to Set Up a Conjoint Study (An Overview)," conjointly, [Online]. Available: How to Set Up a Conjoint Study (An Overview). [Accessed 9 8 2023].

[24] I. Kojčić and M. Kuzmanović, "Conjoint analysis of green consumer preferences for electronic products," *International Journal for Quality Research,* vol. 16, no. 2, pp. 559-575, 2022.