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Factors influencing the choice of brands of music services among Russian consumers

Kseniia Gunko (41205)

Abstract

This paper examines the attitude of consumers towards music streaming services in Russia. The main goal of the research is to define the level of preferences of different features of the services and to match them to the brands present in the market. The data about brand usage and consumer preferences were collected via an online survey on a sample of Russian users of music streaming services. The analysis is split into two parts. Firstly, the importance of the features was defined using Best-Worst Scaling method. Secondly, multinomial logit model was used to predict a brand depending on consumer preferences. Combination of the two steps allow to define a competitive advantage of a particular brand. The results show that despite what was expected, free access shows a low level of importance for Russian users. On the contrary, the most important factor is the availability of all the essential artists in the library of the service. Among the brands which are present in the Russian market, Apple Music has shown the best performance by this feature, which reflects its strong position in terms of brand commitment.

Keywords: Discrete Choice Models, Multinomial Logit, Best-Worst Scaling Method, Music Streaming Services, Brands
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Contents

1 Introduction

The landscape of the recorded music industry is changing rapidly with technological development and innovation. In the end of 90s, music industry revenues consisted exclusively of physical formats. With peer-to-peer services expansion, the industry revenues started declining reaching their lowest in 2014 (IFPI, 2018). Nowadays, revenues are more diversified, with digital accounting for more than half of the total. Within the digital segment, 80% of revenues come from streaming services. Globally, streaming revenues have been sky rocketing over the last decade, reaching 8.9 billion US$ in 2018 compared to 0.3 in 2008 (IFPI, 2018). It's no surprise then that a rapidly expanding market such as this, attracts more and more new players, forcing the current participants to invest not only in market expansion, but also in strengthening brand loyalty.

By definition, brand loyalty is characterized by a consumer's willingness to rebuy a brand and its products or services in the future, causing repetitive same-brand purchase, in spite of external marketing activities which target on causing switching behavior (Oliver 1999). Different authors define various components of brand loyalty, based on functionality, trust, emotions, social aspects, etc (Sweeney & Soutar 2001). In general, it relates to persistence in consumer preferences reflected in a linkage between past and current brand choices (Bronnenberg & Dubé 2017). The approach also varies within the context of the industry (Kim et. al 2011) and the segment of consumers (Shun Yin Lam 2014). Overall, in the digital environment brand loyalty is represented by the factors driving customers' retention decision (Osborne 2011). However, features of music streaming services which influence consumers' decision to switch between brands yet have not been developed.

The purpose of this research project is to determine the factors which shape consumers' loyalty to music streaming services in the Russian market, which has certain peculiarities due to challenges in the development of market economy and legal framework during the post-Soviet period. The motivation for this study was inspired by the industry changes which occurred over the last few years, such as depiratization of vKontakte's music streaming service which was the market leader for over a decade after the launch in 2007. After releasing their legal streaming service BOOM in 2016 and requiring users to pay for content, vKontakte lost its competitive advantage. The app has a very low average rating both on Google Play and Apple Store, presumably not only due to the flaws in the functionality of the app, but also because users were not accustomed to paying for content on vKontakte.

Overall, young people in Russia listen to music regularly. According to Levada-Center, an independent, non-governmental Russian polling and sociological research organization, as of February 2019, nearly 90% of Russians aged 18-39 consume music at least once a month, with over 80% consuming at least 2 to 3 times a week. However, according to FOM (Russian Public Opinion Foundation), in 2016, there were merely 20% of Russian internet users who believed that they should pay for content. Given this context, it was fair to expect that vKontakte's shift to a paid model led to a redistribution of market forces as users started searching for alternatives. Nevertheless, the main inconsistency between forecasts and reality lies in the fact that users switched to paid serviced, anyway.

Understanding why some services are more attractive to consumers than others requires two different components. First of all, it is necessary to define what features are important for consumers when they choose a streaming service. Second, some features may be associated with all brands which are present in the market simultaneously, thus they cannot be considered a competitive advantage. In other words, it is insufficient for a service to be outstanding by a random feature, it has to perform best by the attribute which users find the most important. Best-Worst Scaling method which was used to rank consumers' preferences has allowed to reveal that the most important factors for consumers are availability of all the essential artists in the catalogue of the service and offline access, which was separated from possibility to download music. However, the results of multinomial logit model have shown that vKontakte, Apple Music and Yandex.Music have the same offer in terms of offline access, while Apple Music matches best the criteria of availability of the artists, supporting a revealed high commitment to the brand.

The remainder of the paper has the following structure. The theoretical background highlighting patterns of consumers choice and aspects of brand loyalty are described in Section 2. The overview of the Russian market and a general definition of the music streaming services market are discussed in Section 3. Section 4 presents econometric models underlying the empirical analysis. Section 5 provides details on the survey and data collection, whereas Section 6 contains the results. Section 7 concludes.

2 Literature overview

Digitalization has become revolutionary for the entertainment industry, including both music and motion picture. With technology development, marginal costs associated with production of an additional audio file are approaching zero (Datta et al. 2017). This makes a great distinction from the production of physical goods. Since Napster was founded in 1999, the number of new products brought to the market has increased significantly (Aguiar & Waldfogel 2016). On the demand side, consumers have access to a large volume of content which is not limited by a budget constraint, unlike physical media sources or à-la-carte pricing models. Internet users nowadays have an opportunity to listen to artists from the 'long tail', which they would have ignored otherwise due to unnecessary risks of paying for unpredictable quality. From the suppliers' point of view, low production costs are associated with scale economy. Reduction of entry costs for new products allows the music industry to diversify investments, considering high level of uncertainty at the moment of investments (Aguiar & Waldfogel 2018). By the same token, independent movies more often become commercially successful (Waldfogel 2016). As a general matter, Aquiar and Waldfogel (2016) have recognized an increased level of quality of content stimulated from both demand and supply sides.

Even though the entrance costs for new products are continuously decreasing, competition among companies distributing content is fierce, as the demand of big audience can be sufficiently covered by only a few players (Datta et al. 2017). The market overall is associated with high entrance barriers, such as costs for the users' information storage and concluding agreements with record companies (in particular paying royalties to copyright owners), e.g. even one of the biggest global music streaming services Spotify was launched in India with a limited library, without a catalogue from Warner Music Group, due to the challenges in negotiations with the record label. Moreover, the biggest players have opportunities to perform anti-competitive behavior against each other. For example, Spotify filed an antitrust complaint to the European Commission in March 2019 against Apple's 30% tax on purchases made through Apple's payment system, including upgrade from a free to premium version of Spotify's service.

Nevertheless, even within a small set, consumers do not necessarily perform rationally. Empirical studies show that costs of acquiring product information before an actual purchase are relatively high (Bronnenberg & Dubé (2017). Consequently, consumers often consider only a small subset of the available products. The decision making process follows a 2-step procedure. First, consumers narrow their possible choices to a smaller set of options and then make a final decision within this smaller set (Eliaz et al. 2011). Thus, there are no guarantees that the final choice of a certain brand in fact matches the actual preferences of the consumer. At the same time, companies may push marketing campaigns intended to increase recognition and making the brand more likely to end up in the choice subset. Presence of informational barriers obviously gives an advantage to established brands, but even marketing campaigns do not guarantee conversion to another brand because of the prevalence of switching costs which decrease incentives for consumers to experiment with new products (Hoffman et al. 2017).

Search and switching costs may influence consumers to develop brand loyalty, which is defined as a tendency to repurchase and/or recommend the same brand, despite any marketing efforts or compelling circumstances that could influence a user to switch to another brand. This definition implies the distinction in the concepts of loyalty and satisfaction, in a context that satisfaction is an 'unreliable precursor to loyalty' (Oliver 1999). This idea is aligned with consumers' bounded rationality, which takes origin in a limited capacity of consumers to formulate and solve complex problems, forcing individuals to substitute a utility maximizing option with a *'good enough'* one (Simon 1957). Wernerfelt & Birger (1991) distinguish two types of brand loyalty. 'Inertial brand loyalty' is associated with the absence of information imposing a time lag between the launch of a new product/service and consumers' awareness of its attractive features. 'Cost-based brand loyalty' is related to the costs of switching. In this case, brand utilities are inter-temporally dependent, as the choice of brand is conditional on the previous purchase. In this matter, Bronnenberg et al. (2012) give a more illustrative example of persistence in consumer preferences over time, showing that brand experience early in life has an influence on the brands choice practices throughout the entire lifetime.

In the literature, there are plenty of studies related to brand loyalty. Various authors define different components of brand loyalty which depend on the industry, segment of consumers or general context of the study. Kim et. al (2011) investigate the market of digital items for social networking communities. They use structural equation modelling with a 3-dimensional approach to customer consumption value: functional, emotional and social, originally developed by Sweeney & Soutar (2001). In the study, the authors define that aesthetics and playfulness constructs which represent the emotional block have a significant impact on the intention to purchase digital items. Ching-Hsuan Yeh (2016) uses a similar approach to analyze brand loyalty in the smartphone market. Emotional aspect again had the strongest effect on the brand loyalty, followed by brand identification, functional and social values. It was also shown that social and emotional value show a greater correlation with brand loyalty as age of user increases, while there were no significant differences between genders. Distinction of brand loyalty for early and late adopters was discussed by Shun Yin Lam (2014) through the example of mobile devices. The study shows that the choice of brand for early adopters is driven by brand satisfaction, while late adopters appreciate perceived value, which refers to a brand's overall evaluation relative to what a consumer's expenditure (e.g. the price they pay for the service). It is supported by a different approach which states that price can't be definite since the perception of price for different consumers may vary between the absolute price and subjective balance between price and quality, raising the necessity of weights for different consumers (Zeithaml 1988).

In the environment of digital music Dörr et al. (2013) have updated the constructs to analyze the motivation of consumers to pay for the content, considering that the main functionality (music streaming) is provided for free. The core idea of the study is to reveal the features which may convert users from using pirated services to MaaS. They show that there is a positive effect from the social environments who disapprove of music piracy, that is, pirating music is less prevalent in societies where illegal ownership of music is frowned upon. Another characteristic promoting MaaS against the pirate alternatives is music recommendation based on tags and filtering. Overall, the main output is to encircle features which influence the choice of brands and potentially form brand loyalty.

3 The Music Industry

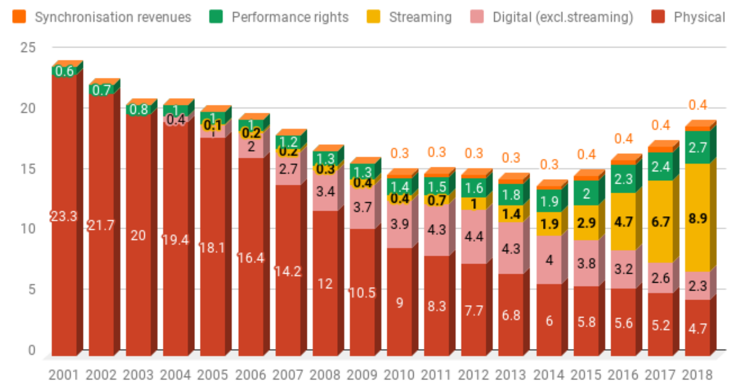
3.1 Market Definition

When analyzing music services, the first step is to define the market. Music service providers have to compete for consumers' attention in multiple ways. First, the consumers not only have varying budget constraints, they also differ in the amount of time spent on consuming entertainment content. This limitation was best illustrated by Netflix CEO Reed Hasting who said that "Sleep is our competition". Within the digital environment, music services compete with movie streaming services, podcasts, radio, just to name a few. These activities are mutually exclusive in that consumers cannot both stream a movie while tuning into their favorite radio station, unlike reading a newsfeed on various social networks, which could be complementary and done simultaneously.

Consumers have to decide between various types of analog and digital consumption options when listening to music. Over the last 2 decades the global revenue of the physical segment dropped from 24 US$ billion in 2001 to 4.7 in 2018. Revenues from streaming have increased from 0.1 US$ billion in 2005 to 8.7 in 2018. Overall, within global revenues in 2018, the physical segment represented only 25% of the total while digital, including subscription, ad-supported streaming and digital downloading makes up 59% (IFPI, 2018). Considering that as of 2018 there were 255 million paid subscription accounts globally, compared to 8 million in 2010, it is reasonable to infer that users are shifting away from the analogue world to a more digital form of consumption.

As Sinclair and Tinson (2017) claim, we are entering a 'post-ownership' economy where users prefer to share rather than physically or digitally own goods and services, also referred to as digital commons (Ghosh, 2006). This introduces several new characteristics to define the landscape of consumption.

Figure 1: Global Recorded Music Industry Revenues 2001-2018, US$ Billion (IFPI, 2018)



More specifically, Sinclair and Tinson (2017) claim that sharing content and the opportunity to project ones' music identity in social media environments is crucial for modern consumers. Nevertheless, the process of dematerialization is far from being finalized, as users still have to choose between analogue or digital copy, and within the latter downloading versus streaming. Ownership still remains an important psychological factor for individuals motivated by a strong emotional connection with owned possessions (Pierce et al. 2003).

The second way to look at consumers preferences is to explore attitudes towards pirated as opposed to legal content. There are two main types of motivations behind piracy. The first group of pirating consumers consider prices to be unfair, or 'religiously believe that everything should be free', therefore refuse to pay for music consumption. These users equate music to other forms of information which should be free (Al-Rafee and Cronan 2006). Music pirates of the second type use illegal downloads in order to listen to a preview of a song before they make a decision whether to buy it or not (Bhattacharjee et al. 2003). Nevertheless, the concept of music piracy may eventually become outdated due to changes in the industry. The development of the concept Music as a Service (MaaS) has made piracy a less attractive alternative. Free ad-based versions made users who rejected legal content due to high prices switch from pirate services (Dörr et al. 2013). At the same time, many streaming services provide the option of audio preview, making the piracy of the second type irrelevant.

Overall, it is a complex task to define the relevant market, especially considering a multidimensional approach described above. To narrow down the options, this research uses a definition of the European Commission (EC), which is motivated by a clarity of the definition and lack of the own one in Russian practice. According to the definition of the EC, the relevant product markets are "comprised of all those products and services which are regarded as interchangeable or substitutable by the consumer, by reason of the products' characteristics, their prices and their intended use". In a way, defining the relevant product market within the digital environment is challenging because the substitutional analysis around price responses does not provide much information as the prices of music consumption sometimes can be zero (for free price plan). However, the commission's assessments presented in several cases related to the music industry establish precedents which define a proper relevant product market.

In case No COMP/M.5272 - Sony/ Sony BMG (2008) resolved by the EC, the commission has identified a clear distinction between digital and physical music formats. It was found that from the demand side prices for a digital audio recording prices are usually lower than for the physical ones. At the same time from the supply perspective the structure of the digital market differs from the physical segment in terms of 'organization, technical and commercial conditions, marketing and cost structure'. Nevertheless, the EC does not find a segmentation by downloading and streaming services relevant following the Notifying Party statement that 'music services can in principle offer both download and streaming services and that there are no significant barriers or costs for such supply-side substitution' (Case No COMP/M.6458 - Universal Music Group/ EMI Music, 2012).

Furthermore, the EC suggests illegal music should be distinguished from the wholesale market of the recorded music. Even though there is a certain degree of substitution as well as complementation between legal and pirated content from the users' point of view, these factors are not relevant for music retailers who do not have the flexibility to switch between these 2 types of music delivery methods within a 5-10% price increase. The same issue affects record companies on the supply side, as they will not start producing illegal music given any level of price reduction. Thus, following this definition this study is focused exclusively on legal services, and excludes any pirate services (e.g. torrent trackers). Similarly, radio as a music delivery method is also excluded from this analysis as it lacks the possibility for consumers to play desired music on demand. To conclude, following the definition, the market explored in this study is the market of legal music services which allow users to listen to music on demand with or without downloading content to the device memory.

In addition to the product market, the second step is to define the relevant geographic market. According to the European Commission, a relevant geographic market "comprises the area in which the undertakings concerned are involved in the supply and demand of products or services, in which the conditions of competition are sufficiently homogeneous and which can be distinguished from neighbouring areas because the conditions of competition are appreciably different in those areas". In particular, in Sony/BMG (2008) the commission has concluded that the wholesale market for digital recorded music is national. The European Commission specifies that due to the development of the internet which opens new possibilities of types music distribution, there are indications to expand towards multi-territorial market, but this 'evolution is very much on-going'. The main barrier is reaching agreements with record companies that are concluded on a national level. Even the largest digital customers such as Spotify and Apple are not present in all EEA countries due to the complications involved in reaching these agreements (Universal Music Group/EMI 2012).

Considering this prescription, the Russian market could be expanded to a post-Soviet market (Commonwealth of Independent States). Nevertheless, the main peculiarity of the Russian digital market is defined by the introduction of the Federal Law No. 242-FZ 'Amending Certain Legislative Acts of the Russian Federation as to the Clarification of the Processing of Personal Data in Information and Telecommunications Networks'. The law came into effect on September 1, 2015 and requires operators to guarantee the processing (i.e. recording, systematization, collecting, updating and changing) of personal data of Russian Federation citizens with the use of the servers located on the territory of Russian Federation. Moreover, operators must notify the Roskomnadzor (Federal Service for Supervision of Communications, Information Technology and Mass Media) of the location of the servers with the stored databases. The introduction of this law was one of the motivators that resulted in cancelling Spotify's 2015 launch in Russia. The official announcement was made by Alexander Kubaneishvili who was hired by Spotify to lead the Russian division, who stated, ”I regret to inform you that Spotify refused to launch in Russia in the foreseeable future. There are several reasons - the economic crisis, the political situation, the new laws governing the internet”. Thus, the analysis is narrowed down to brands that currently exist in the Russian market, because even if the agreements were not upheld on the national level between record companies and digital customers, the restriction creates a barrier for the Russian market to expand beyond the national level.

To sum up, the definition of the European Commission helps to shrink the range of music streaming services to legal streaming services, which allow to play music on demand and are currently available for the Russian consumers without a necessity to bypass geo-restrictions.

3.2 Overview of the Russian Market

To understand the behavior of consumers, it is important to have a clear sense of their background. As any other market, Russia has its own peculiarities which form the mentality and allow to recognize habitual patterns. This section provides a short overview of Russian modern history related to the development of the music market, explains the reasons behind the expansion of the demand for pirated content and describes the current status of the Russian music streaming services market.

The Russian audio and video market has developed under a range of institutional factors which take their origin back to the USSR. Since Soviet government had monopoly rights over distribution of content, everything in conflict with party ideology was considered illegal. Overall, media consumption was shaped by censorship, rather than price. As a result, people formed an alternative consumption behaviors, smuggling vinyl records and or listening to unauthorized broadcasting stations (e.g. Voice of America, BBC Russian Service and RadioLiberty in mass media were called 'voices of the enemy'). These types of behaviors were peculiar forms of protest against the isolation of the Soviet regime (Kiriya 2012). After the dissolution of the Soviet Union, people got free access to Western content for the first time, which was associated with the process of democratization. In the first decade of the newly formed country, channels of legal content distribution were limited and did not manage to satisfy the increased demand, thus piracy became an unexpected consequence of Perestroika (Mickiewicz 2001). Attempts to restrict the access to the illegal content were perceived as a return to censorship. Moreover, the concept of illegal content was unclear, as there was no distinction between legal and pirate content. All that mattered is that information was 'accessible' (Beumers 1999). Kiriya & Sherstoboeva (2015) claim that legal frameworks were imported to Russia, which created inconsistency between formal and informal institutions, triggering informal practices of media consumption due to social acceptance.

In Social Science Research Council's (SSRC) study on Media Piracy in Emerging Economies (2012), Sezneva & Karaganis have distinguished three main periods of content regulation. The first period between 1991 and 1999 is characterized by weak copyright legislation, a low level of awareness of copyright infringement by society and a high volume of optic discs and compact audio cassettes smuggling, especially from the countries of the former Eastern Bloc. By the late 90s channels of distribution for pirate media were already formed. Thus, the period until 2006 is described by the substitution of smuggling with domestic production in order to decrease operating costs. At the same time, during negotiations to join WTO, the international community pressured Russia to make legislative changes to protect copyrights. The period after 2006 is characterized by the development of the internet and peer-to-peer services, the latter of which have become the main competitor to physical copies of records. At the same time, music industry groups and the state started to cooperate on copyright protection. On January 1 2008, Part 4 of the Civil Code regulating *the right to products of intellectual activity and means of individualization* took effect.

A few years later, the fight against piracy reached a new level when in February 2010 the biggest torrent-tracker *torrents.ru* was blocked by the decision of governmental authorities. This case became the first precedent of website blocking in connection with copyright infringement. On August 1 2013, the new Federal Law No. 187-FZ concerning the Protection of Intellectual Rights in Information and Telecommunication Networks was introduced. In mass media, this law was called 'antipirate', as it allowed to block websites with pirate content. However, in the environment of tightening the legislation, internet-users, or consumers, were excluded from the scope of the law. In other words, downloading or consuming the pirate content is not considered illegal, even though originally there were discussions about implementations of penalties for users too by tracking their IP address.

In the midst of the antipiracy campaign, a new phenomenon emerged. Founded in 2006 by Pavel Durov, vKontakte originally was an ordinary social network, sometimes even called 'Russian Facebook'. However, in 2007 vKontakte introduced a feature of uploading music and video content, which eventually made the social network one of the biggest libraries of pirate content. Every year between 2011 and 2016, the Office of the U.S. Trade Representative (USTR) named vKontakte 'among worst piracy offenders' in its annual Special 301 Report. Even with this status, vKontakte was protected by the Russian courts which in most cases dismissed the plaintiffs' claims, indicating that the social network is only an intermediary, while it is the users who upload the content who should bear responsibility. In 2014, three major labels, Sony Music Russia, Universal Music Russia and Warner Music UK filed separate law suites against vKontakte for large-scale music piracy, demanding 51 mln rubles ($\sim$1 mln \$US, average exchange rate in spring 2014). In 2015, Sony dropped complaints reaching a confidential settlement with vKontakte. The trial with Universal and Warner finished a year later, in 2016, with the victory of vKontakte.

In an official statement in 2014, RIAA's former Executive Vice President, Neil Turkewitz, said "For the fourth year in a row, the U.S. government has called out vKontakte. We hope that vKontakte's new management will quickly distance itself from its predecessors and will either become a licensed distributor of music or dismantle its infringing music service". In particular, Turkewitz was specifically referring to the latest changes in vKontakte's ownership structure. In January 2014, the founder of vKontakte Pavel Durov sold his stake in the company and 3 months later left the company and the country. In the meantime, the new management introduced a new antipiracy strategy and actively started removing illegal content from the library to the open irritation of users, who were not used to paying for the content. According to FOM (Russian Public Opinion Foundation), only 22% of Russian internet users believe that they should pay for content, while 52% think exactly the opposite (2016). This rate hasn't changed since 2013.

In April 2016, vKontakte launched the first version of its legal streaming music service 'Music VK', developed by United Media Agency. To legalize vKontakte, UMA has managed to complete agreements with Sony Music, Warner Music, Universal Music, local recording studios 'Soyuz' and 'Nikitin' and music distributor Orchard. Half a year later, UMA conducted rebranding, introducing a new mobile application BOOM, operating in accordance with a freemium price model, which offers two price plans, free for access to limited features or premium. Over the next year, BOOM implemented several restrictions to motivate users to convert from free to premium users, in particular, limited duration of listening to music to only 30 minutes a day. By December 2018, BOOM reached 2.1 mln paid or trial subscribers, according to an audited report of Mail.Ru Group Limited, the current owner of vKontakte.

There is no exact open source information about the total size of the premium segment of music streaming services market. However, the approximate estimate at the beginning of 2019 was 5 mln paid users. The biggest players in the market are Apple Music (launched in Russia in 2015), Yandex.Music (founded in 2010) and YouTube Music (launched in 2018, which includes Google Play Music). Yandex.Music accounted for 1 mln paid subscribers in June 2018. Other companies do not reveal this information in open sources. All services, except for Apple Music, run a freemium pricing model, providing a choice to the customers, whether to pay and use the full version of the service or to use a free option with limited features. Apple Music offers only a premium model. Price for a standard price plan of the apps lies between 149 and 169 rubles (∼2US$) for a monthly subscription compared to ∼10US$ for Apple Music, Spotify or Pandora premium accounts in the US. Such a low level of price dispersion in Russia does not allow to estimate price elasticity, but only to counterpose premium price plan against free access.

4 Empirical Approach

The purpose of this research is to define the reasons which lie at the root of consumers' choice. It is not enough to understand how brands perform relative to each other, but whether or not these differences are appreciated by the consumers. Thus, the main goal of the study can be decomposed into two questions, namely what features allow consumers to distinguish brands from each other and which of those features are important for them. The first question is answered with the help of multinomial logit, which illustrates a decision-making process within a set of alternatives, given characteristics of a decision-maker and features of the alternatives. The second question uses Best-Worst Scaling method which allows to rank the importance of different attributes. The following two subsections describe these models in detail.

4.1 Multinomial Logit

Discrete choice models are a family of models representing the behavior of a consumer who makes a choice from a set of alternatives. To use discrete choice models, the choice set should follow 3 conditions: i) the items in the set should be mutually exclusive. ii) the choice set should be exhaustive, implying that a consumer does not have a possibility to make a choice outside the set. iii) the number of choices has to be finite. Discrete choice models are consistent with utility maximization and follow the concept of Random Utility Models.

Random Utility Models were first discussed from a psychological perspective in order to interpret inconsistencies of consumers' behavior in their decision making processes. The concept was first proposed by Thurstone (1927) based on pairwise comparison of a series of tested features (stimuli). Block and Marschak (1959) proposed a definition of choice consistency, considering the existence of such an alternative which maximizes the utility within a feasible set. In the next class of models, utilities were treated as random variables due to unobserved factors, rather than a lack of rationality of decision makers (McFadden 1968/1976).

The model is derived in the following manner: a consumer n makes a choice within j alternatives from the set $j = 1 \ldots J$. The utility of a consumer n from the choice j is labeled U_{nj}. It is assumed that a consumer makes a choice j only if it maximizes the utility among all possible alternatives. No one except for the consumer himself knows the actual utility, thus variable U_{nj} is latent. However, a set of characteristics of the alternatives x_{nj} and attributes of the decision maker s_n are visible to a researcher. Based on the observed characteristics, it is possible to decompose the utility U_{nj} into 'representative utility' $V_{nj} = V(x_{nj}, s_n), \forall j$ and a stochastic component ϵ_{nj}. In other words, $U_{nj} \neq V_{nj}$ due to unobserved factors. The joint density of the random vector $\epsilon = \{\epsilon_{n1} \ldots \epsilon_{nJ}\}$ is denoted as $f(\epsilon_n)$. In the environment where consumer n maximizes their utility, the probability of choosing alternative i over alternative j, is presented by the following expression:

$$\begin{aligned}
P_{ni} &= Prob(U_{ni} > U_{nj}, \forall i \neq j) && (1)\\
&= Prob(V_{ni} + \epsilon_{ni} > V_{nj} + \epsilon_{nj}, \forall i \neq j) && (2)\\
&= Prob(\epsilon_{nj} - \epsilon_{ni} < V_{ni} - V_{nj}, \forall i \neq j) && (3)\\
&= \int_{\epsilon} I(\epsilon_{nj} - \epsilon_{ni} < V_{ni} - V_{nj}) f(\epsilon_n) d\epsilon_n && (4)
\end{aligned}$$

where $I(\cdot)$ is the indicator function which takes a value of 1 if the expression in the parentheses is true and 0 otherwise. The distribution $f(\epsilon_n)$ in fact represents the unobserved component spread for the entire population of individuals with the same observed value. Thus, the integral grasps the outcome of all possible values of the stochastic component.

There are several ways to evaluate the integral depending on its form. In particular, a closed form integral is derived in case of a logit model, including multinomial and nested logit. The convenience of using closed formed integrals is that they allow for the calculation of probabilities analytically rather than by running simulations. In addition, the analytic form allows a simple interpretation of coefficients.

From the probability expression it is clear that only the difference in the utilities matter, not the absolute values. This characteristic has two implications. First, all specifications with the same difference are equal, so adding constants to both utilities will not change the probabilities. Second, as the scale does not play a role, multiplying the utilities by the same factor will not influence the final result, either. Moreover, to make the model properly identified, parameters of one of the alternatives should be normalized to zero, making this alternative a reference.

As mentioned earlier, there are two type of variables which can be observed, i.e. a set of characteristics of different alternatives and attributes of the decision maker. Thus, representative utility can be decomposed into individual-specific (s_n) and alternative-specific variables x_{nj}:

$$V_{ni} = \alpha_i + \mathbf{x}'_{ni}\boldsymbol{\beta} + \mathbf{s}'_n\boldsymbol{\gamma_i} \tag{5}$$

where α_j is an alternative-specific constant which captures the average utility of the factors not included in the model, normalizing ϵ_{nj} to zero; vector $\boldsymbol{\beta}$ assigns the effect of each alternative-specific variable to the individual's utility; $\boldsymbol{\gamma_j}$ is a vector parameter which represents how individual characteristics influence the utility in case of choosing option j. It should be noted that there is only one coefficient β for an alternative-specific variable, while γ_j is unique for every alternative j.

It is assumed that in the logit model errors are distributed i.i.d. extreme value, which is also called Gumbel distribution or type I extreme value. Errors are considered independent in the sense that information about one error doesn't give information about the error of another alternative. In such a manner, everything not identified in the model is 'white noise'. Under this assumption, density and cumulative distribution functions are expressed as follows:

$$f(\epsilon_{nj}) = e^{-(\epsilon_{nj}+e^{-\epsilon_{nj}})} \tag{6}$$

$$F(\epsilon_{nj}) = e^{-e^{-\epsilon_{nj}}} \tag{7}$$

Recalling that $P_{ni} = Prob(\epsilon_{nj} < \epsilon_{ni} + V_{ni} - V_{nj}, \forall i \neq j)$ is in fact a cumulative distribution and assuming that ϵ_{ni} is given, the probability of choosing alternative i is the product of individual cumulative distributions:

$$P_{ni}|\epsilon_{ni} = \prod_{i \neq j} e^{-e^{-(\epsilon_{ni}+V_{ni}-V_{nj})}} \tag{8}$$

Nevertheless, as error ϵ_{ni} is not observed, the probability is then expressed as the conditional probability weighed over the density function $f(\epsilon_{nj})$:

$$P_{ni} = \int \Big(\prod_{i \neq j} e^{-e^{-(\epsilon_{ni}+V_{ni}-V_{nj})}}\Big) e^{-(\epsilon_{nj}+e^{-\epsilon_{nj}})} d\epsilon_n \tag{9}$$

This choice probability, according to McFadden (1973), is simplified to the analytic solution:

$$P_{ni} = \frac{e^{V_{ni}}}{\sum_j e^{V_{nj}}} \tag{10}$$

This presentation of the probability holds several convenient properties. First, the probability takes values in the interval of 0 (not included) and 1 (in case of only one alternative). Second, the increase of the representative utility V_{ni} increases the probability of choosing alternative i and vice versa. Third, the sum of all probabilities equals 1: $\sum_{i=1}^{J} P_{ni} = \frac{\sum_i e^{V_{ni}}}{\sum_j e^{V_{nj}}}$, as the decision maker necessarily makes a choice of one of the feasible options. Finally, since the relation of the representative utility to logit probability is not linear, but S-shaped, it reflects the fact that if utility of one of the choices is far more superior than other, the further increase of the utility will have only little marginal effect on the probability of choosing this alternative.

However, multinomial logit has a strong restriction that errors are independent identically distributed. IID condition implies that the unobserved portion of utilities about one alternative does not give any information about the error in utility for another alternative. In practice this assumption does not necessarily hold. Red/Blue bus paradox is one of most commonly used examples, originally proposed by McFadden (1973). Assume, that an individual can choose between two types of transport to get to work, a red bus and a car. Probability of each option is 1/2 and the odds of choosing one type of transport over another is $\frac{1/2}{1/2} = 1$. The assumption of the independence of irrelevant alternatives (IIA) implies that if a new alternative appears in the choice set, the odds for the old alternatives remain the same. In other words, the probabilities have to adjust in such a manner, that their ratio does not change. However, if a Blue bus is introduced, it is fair to expect that Red and Blue buses have equal probabilities. Moreover, for an individual Blue and Red buses represent one options 'a bus', which is chosen with probability 1/2. Thus, probability of choosing each bus is 1/4, and the odds of choosing a Red bus over a car are now $\frac{1/4}{1/2} = 1/2$, which is a different result compared to a scenario with only two vehicles.

If IIA does not hold, Generalized Extreme Values models are used. In particular, if a choice set can be split into groups (nests) in such way that IIA holds within each subset and IIA does not hold for the alternatives in different subsets, nested logit model is considered an appropriate choice. In case of nested logit, probability in the model with K nests is presented in the following form:

$$P_{ni} = \frac{e^{V_{ni}/\lambda_k} \left(\sum_{j \in B_k} e^{V_{nj}/\lambda_k} \right)^{\lambda_k - 1}}{\sum_{l=1}^{K} (\sum_{j \in B_l} e^{V_{nj}/\lambda_l})^{\lambda_l}} \tag{11}$$

where B_k represents a nest k and parameter λ_k measures the degree of independence in unobserved part of utility within nest B_k. If $\lambda_k = 1$ for all nests, implying complete independence, nested logit reduces to a standard logit model (Train 2009).

4.2 Best-Worst Scaling

There is substantial work in economics on consumer demand. This includes demand estimation with homogeneous products and discrete choice demand models. These models typically estimates own- and cross-price elasticities of demand and back-out information about unobserved quality (Genesove and Mullin 1998; Berry 1994). There is also an extensive literature in quantitative marketing (Bronnenberg & Dubé 2017). Other methods include rankings, ratings or top-boxes (Goodman et al. 2005).

Nevertheless, asking consumers about their preferences directly, and thus focus on stated preferences gives biased and consequently unreliable results. First, respondents are not restricted in their choice by discriminating one of the options in favor of another (Lee et al. 2007). Second, they show greater tendency to agree rather than disagree with items independent on the context (Billiet & McClendon, 2000). Third, people more likely operate within extreme categories of choice, which is expressed by the phenomenon called Extreme Response Style (Baumgartner Steenkamp, 2001). All these flaws result in similarities in means, making the interpretation inaccurate.

Introducing the necessity of trade-off, pairwise comparison solves all these problems, however it results in a large number of questions. For example, comparison of 13 attributes gives 78 pairs, which is too much for a typical survey. Finn & Louviere (1992) have proposed and alternative method of choice-based measurement, inspired by real-life patterns of consumers' decision-making process. Best-Worst Scaling method recognizes three different cases. In case 1, also called maximum differentiation (maxdiff), respondents choose one best (most preferable or most important) and one worst object within subsets of objects/ features (Finn & Louviere 1992). Case 2 is the profile case, where respondents identify the best and the worst feature in the proposed profile (Louviere et al. 1994). Case 3 is multi-profile, where respondents evaluate the best and worst profile designs (Marley & Pihlens 2012).

Table 1: Best-Worst Scaling cases

(a) BWS, case 1

MOST	**attribute**	**LEAST**
✓	Price plan	○
○	Offline mode	○
○	Library	○
○	Sound quality	✓

(b) BWS, case 2

		MOST	**LEAST**
Price plan	*premium*	○	○
Offline mode	*stored in cache*	✓	○
Library	*30 mln tracks*	○	✓
Sound quality	*320kbps*	○	○

(c) BWS, case 3

	Brand˙1	*Brand˙2*	*Brand˙3*
Price plan	premium	free	premium
Offline mode	yes	yes	no
Library, mln tracks	16	45	35
Sound quality	320kbps	96kbps	160kbps
MOST	✓	○	○
LEAST	○	✓	○

Case 1 (maxdiff) is considered to be the baseline of the entire family of the models. It was exploited almost exclusively before 2005, both in academia and market research environments. Cases 2 and 3 were regarded as the extensions and did not receive much attention until mid 2000s. Nowadays, these models are widely used in economics and healthcare fields (Flynn & Marley 2014). The main purpose of maxdiff is positioning objects from the set on the respondent's subjective scale of importance or interest (Auger et al. 2004). Cohen and Markowitz (2002) have shown that there is no bias in the rating scale due to the restriction of only one best and one worst choice in each subset.

The first step to conduct BWS study is to create the sequence of subsets. One of the most common statistical approaches is to construct the sets using balanced incomplete block design (BIBD) developed by Yates (1940). The concept of BIBD ensures that within a set of features of size J i) the subsets are of equal size. ii) each feature appears equal amount of times over the entire experiment. iii) each feature J co-appears with other features *(J-1)* equally often.

The results can be analyzed in two different ways, calculating directly from the data or using more sophisticated approach using multinomial logit. The first method counts 'best' and 'worst' scores of item i (frequency of the item to be chosen as the best and the worst feature across all subsets) on disaggregated level (by an individual n) and on total level:

$$BW_{in} = B_{in} - W_{in} \tag{12}$$

$$BW_i = \sum_n BW_{in} \tag{13}$$

The modelling approach is derived from the idea of utility maximization. Overall, in set M of m items there are $m \times (m\text{-}1)$ combinations with item i selected as the best option and j ($i \neq j$) selected as the worst. Probability of item i to be chosen as the best conditional on item j to be chosen the worst implies the maximum utility difference between these two items:

$$Prob(i = best|j = worst) = \frac{e^{V_i - V_j}}{\sum_{p,q \subset M, p \neq q} e^{V_p - V_q}} \tag{14}$$

As a result, a share of preference of item i calculated using conditional logit model choice rule (Aizaki et al. 2014), considering that all shares sum up to 1:

$$SP_i = \frac{e^{\beta_i}}{\sum_{m=1}^{M} e^{\beta_m}} \tag{15}$$

Even though these two approaches have a significant difference in the level of sophistication, Flynn et al. (2013) note that if the sets are balanced in accordance with BIBD, the estimates and associated R-values of conditional logit model are consistent with the best-minus-worst scores. In other words, considering the relative position of the objects on the preference scale, the results are similar independent on the method of data analysis.

5 Data

5.1 Survey

An online survey was conducted between April 16 and April 30, 2019. The survey was programmed using Qualtrics Platform. The original language of the survey is Russian, with translation to English for reporting of the results. Respondents were recruited via snowball sampling method which implies that respondents who have already taken the survey recruit others who possess characteristics which constitute the research interest (Biernacki & Waldorf 1981). However, this approach imposes limitations on the sample type. Thus, the results cannot be representative for the entire population, but merely for the 18-40 years old who reside in large cities and have a higher level of income. Participants were filtered only by two screening questions: whether they have been living in Russia over the last year and whether they have been using music streaming services or music applications over the last month.

5.2 Questionnaire Design

The questionnaire was split in several blocks. The first block contained questions required for MaxDiff with 13 attributes (see Table 2). The choice sets were constructed in accordance with BIBD, which ensures that each of 13 sets has the same amount of items, each attribute shows up an equal number of times and all possible combinations of choices are shown an equal number of times (see Table 3).

Table 2: Attributes for MaxDiff

no.	Attributes in Long Form	Variable Names
1	Free access	free
2	Lack of advertisement	adv
3	Offline access	offline
4	Possibility to download a track to the device memory	download
5	Possibility to share music tracks outside the music app	share
6	Wide range of playlists (e.g. catalogues by genre)	catalogues
7	User-friendly interface	interface
8	Possibility to skip unlimited number of tracks	skip
9	Music recommendations that match my taste	reco
10	High sound quality	sound
11	The app works properly/ no crash or bugs	bugsf
12	All the essential artists are available in the library	library
13	Is used by many of my friends	friends

In the second part, respondents answered questions about awareness and usage of brands. Overall, 7 brands available in the Russian market were tested along with the option 'other' and 'none of above', which are required for making the choice set exhaustive. In the third block, respondents evaluated the brands they have ever used by the features from MaxDiff block. However, some of the features are considered objective and cannot be evaluated as more or less preferable by brands, such as 'free access' or 'offline access', which are oftentimes contingent on features available in different tiers of price plans. Thus, in order to avoid respondents' misinterpretation and hence a bias in the results, these attributes were coded automatically during data processing. The last group of questions represent respondents' attitude towards music in general and their demographic characteristics. The complete questionnaire can be found in Appendix A.

Table 3: Balanced Incomplete Block Design

Choice set no.	Feature 1	Feature 2	Feature 3	Feature 4
1	4	7	8	9
2	2	8	11	12
3	1	4	6	12
4	2	3	6	9
5	1	9	11	13
6	5	9	10	12
7	3	7	12	13
8	5	6	7	11
9	1	2	7	10
10	6	8	10	13
11	3	4	10	11
12	1	3	5	8
13	2	4	5	13

5.3 Sample

Out of 301 people who opened the link to the survey, 164 met screening criteria and completed the survey. Of these 164, 1 was not considered due to their lack of use of any of the listed brands including ’other’ and 6 respondents were outside of the age range of interest, 18-40. The age group was split between 18-29 and 30-40 years old and crossed with gender. However, there was an overrepresentation of women aged 18-29 in the respondent pool, which makes the total database imbalanced. In order to form sample groups that were representative of the subset of the Russian population this study focuses on and thus correct the sampling bias, weights were applied. These resulting weights reflect actual shares of internet users living in Russian cities with populations over 100,000 inhabitants. Data on population shares were provided by Mediascope WEB-Index. A summary of these shares is presented in Table 4. However, jumping ahead it should be noted that weights do not have a big impact on the results, as usage and awareness rates as well as multinomial logit coefficients do not differ significantly (see Appendices C and D).

Table 4: Weights

	Group	**Population shares**	**Sample shares**	**Weights**
1	Men 18-29	0.198	0.166	1.196
2	Men 30-40	0.284	0.229	1.237
3	Women 18-29	0.202	0.357	0.565
4	Women 30-40	0.317	0.248	1.275

6 Results

6.1 Best-Worst Scaling Results

The study uses Best-Worst Scaling method which allows to understand the importance of different features of music streaming services. In every subset of features respondents chose which attribute was most important (best) and which was least importance (worst). The count approach then shows the number of times each feature was chosen by either characteristic. Best-worst score is calculated as subtraction between best and worst counts for each attribute. Since attributes were shown to respondents 4 times, the range of best-worst scores for every feature lies in a range of -4 and +4, where -4 indicates that the feature was chosen as the worst every time it showed up and +4 indicates the feature was chosen as the best every time. Overall, there were 13 choice sets and every choice set consisted of 4 features, allowing to show all possible pairs of features. The individual results were aggregated in order to present relative importance for each attribute, considering that the higher mean presents the overall higher importance and vice versa. Figure 2 presents the relation between the means of the attributes scores and their standard deviation.

Table 5: BWS, Count Approach

Rank	Attributes	Var	B	W	BW
1	All the essential artists are available in the library	library	296	36	260
2	Offline access	offline	286	57	229
3	The app works properly/ no crash or bugs	bugsf	224	77	147
4	High sound quality	sound	206	63	143
5	Lack of advertisement	adv	201	134	67
6	User-friendly interface	interface	116	65	51
7	Possibility to download a track to the device memory	download	184	134	50
8	Possibility to skip unlimited number of tracks	skip	142	103	39
9	Wide range of playlists (e.g. catalogues by genre)	catalogues	117	173	-56
10	Music recommendations that match my taste	reco	115	175	-60
11	Free access	free	111	229	-118
12	Possibility to share music tracks outside the music app	share	35	313	-278
13	Is used by many of my friends	friends	8	482	-474

The count analysis shows that it is highly important for respondents to have all the essential artists in the library of a music service, which is followed by offline access. Further, it is important for respondents that an app works properly, without crash and bugs and has high sound quality, which show similar means. The least important factors, with the lowest means, are usage by friends and possibility to share music outside the app. Moreover, *library* also has a relatively low variance, indicating that the importance of this attribute does not vary largely among individuals.

Figure 2: Aggregated BW Scores

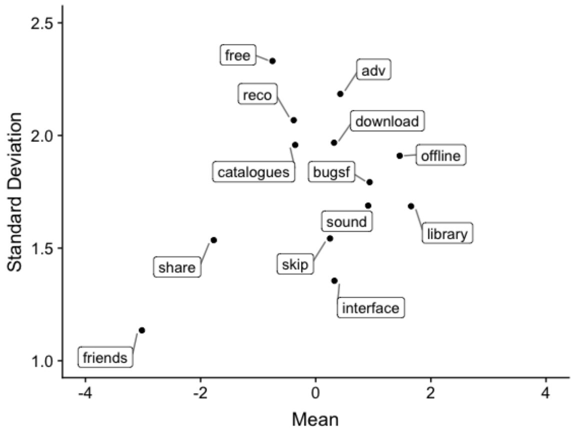
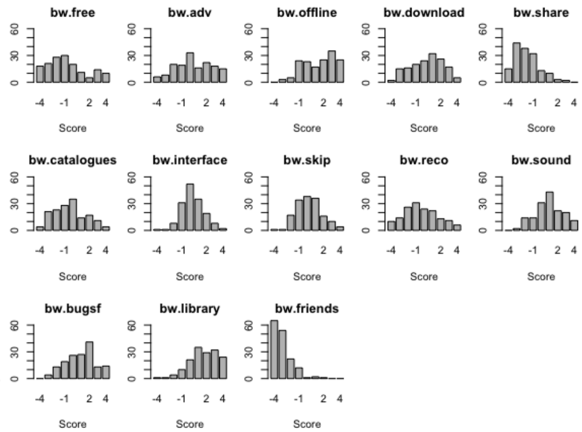


Figure 3: Distribution of BW scores



Similarly, as seen in Figure 3, items *friends* and *share* skew negative, indicating respondents consistently ranked these features as least important, while scores for *offline*, *bugs free* and *library* tend to lean towards positive values. Here it is seen, that even though *free access* and *lack of advertisement* have means close to zero, the deviation is high, as they have relatively high shares of respondents choosing extreme values on both sides of the scale. This peculiarity indicates that overall users are not persistent with their perception of these attributes.

For every subset of 4 features, there are 12 possible combinations, where one feature can be ranked as the most important and one as the least important, because each of 4 features has 3 alternatives. Every respondent evaluates the utility received from considering options i and j as the best and the worst, respectively, and chooses such a combination which maximizes the difference of these utilities. The multinomial logit model represents the probability of each of these scenarios within each subset is presented by equation (14).

For a proper specification of the model, one of the coefficients and hence the utility of the worst option is normalized to zero. The coefficient for omitting could be chosen arbitrary, but it is more convenient to assign the worst option to zero for a more accurate interpretation of the outcome. As the result, the representative utility for an individual n is described as follows:

$$V_n = \beta_1 * free + \beta_2 * adv + ... + \beta_{12} * library \tag{16}$$

Vector $\boldsymbol{\beta}$ contains coefficients for all items, considering normalizing one of the coefficients to zero. The parameters are estimated by the maximum likelihood estimation. Note, that the utility contains only alternative-specific parameters, since each respondent assigns a value to each of the features. Thus, it is relevant to omit an alternative specific constant and keep only generic coefficients (Croissant 2012). The dependent variable of the model takes two values, 1 and 0, where 1 represents that the pair was chosen within each choice set, and 0 otherwise. The number of observations for the model is a multiplication of a number of respondents and a number of choice sets, in this study, 157 and 13, respectively, which gives 2041 observations in total. Since one of the coefficients has to be assigned to zero, parameter *friends* is chosen as a reference, following that it was found the least important using the count approach. Individual-specific attributes, such as age or gender, are not considered in this specification. Multinomial logit coefficients are presented in Table 6.

Table 6: BWS, Model Approach

	Dependent variable:
	RES
free	1.584*** (0.105)
adv	2.278*** (0.107)
offline	2.830*** (0.110)
download	2.227*** (0.107)
share	0.943*** (0.104)
catalogues	1.791*** (0.105)
interface	2.156*** (0.106)
skip	2.174*** (0.107)
reco	1.795*** (0.106)
sound	2.535*** (0.109)
bugsf	2.535*** (0.108)
library	2.956*** (0.111)
Observations	2,041
Log Likelihood	−4,237
Note:	*p<0.1; **p<0.05; ***p<0.01

All coefficients are significant and positive, which gives an additional proof that usage of the services by friends is the least important factor. To check the goodness-of-fit of the multinomial logit model, McFadden ρ^2 is used:

$$\rho^2 = 1 - \frac{log(L_c)}{log(L_{null})} \tag{17}$$

where L_c is the log-likelihood of the current fitted model and L_{null} is the log-likelihood of the null model, which implies that every outcome is predicted with the same probability. Thus, in the case of the current specification of the model, likelihood is calculated as follows

$$L_{null} = \left[\left[\frac{e^0}{\sum_{i=1}^{J} e^0}\right]^N\right]^M \tag{18}$$

where J is the number of alternatives within each subset, N is the number of respondents and M in the number of choice sets. In this model, null log-likelihood is equal to $-13 * 157 * log(12) = -5072$, and

$\rho^2 = 1 - \frac{-4237}{-5072} \approx 0.165$. Even though McFadden's ρ^2 is relatively low, it does not mean necessarily a bad fit of the model. McFadden himself interpreted the coefficient as follows: "While the R^2 index is a more familiar concept to planners who are experienced in ordinary regression analysis, it is not as well behaved as the ρ^2 measure, for maximum likelihood estimation. Those unfamiliar with the ρ^2 index should be forewarned that its values tend to be considerably lower than those of the R^2 index and shouldn't be judged by the standard of the "good fit" in ordinary regression analysis. For example, values of .2 to .4 for ρ^2 represent excellent fit" (McFadden 1977).

However, the coefficients cannot be interpreted by their magnitude, as it is not a linear model. Instead they can be used to calculate the odds of choosing feature i more important compared to another feature j. After aggregation, the odds are presented in the form of the share of preferences, which are summed up to 1 (equation 14). Table 7 represents the results of the calculation of shared preferences made with the model approach. In practice, the coefficients imply that the availability of the artists in the library is twice as important as lack of advertisement (0.162/0.082) and 20 times more important than usage by friends (0.162/0.008).

Table 7: Shares of Preference and Ranks

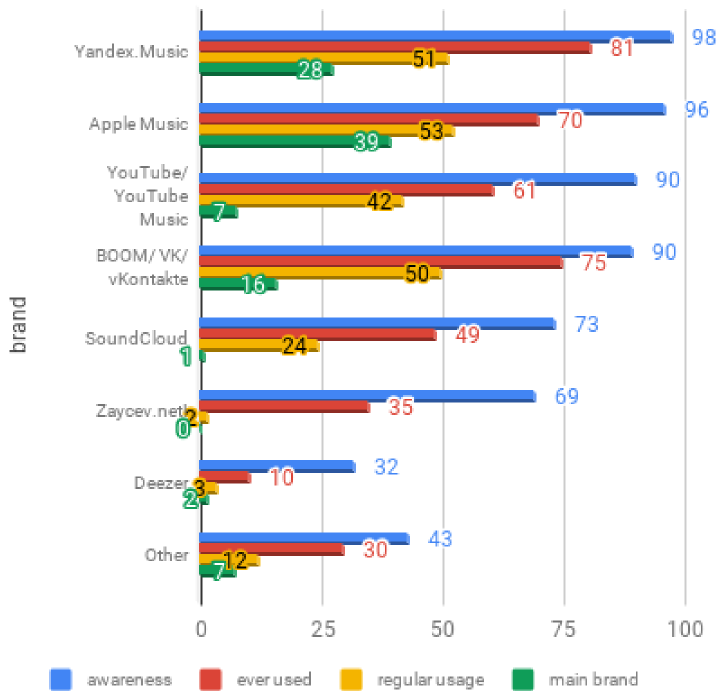
Attributes	Var	Rank (count)	Rank (model)	Importance
All the essential artists are available in the library	library	1	1	0.162
Offline access	offline	2	2	0.143
The app works properly/ no crash or bugs	bugsf	3	3	0.107
High sound quality	sound	4	4	0.107
Lack of advertisement	adv	5	5	0.082
User-friendly interface	interface	**6**	**8**	0.073
Possibility to download a track to the device memory	download	**7**	**6**	0.078
Possibility to skip unlimited number of tracks	skip	**8**	**7**	0.074
Wide range of playlists (e.g. catalogues by genre)	catalogues	**9**	**10**	0.051
Music recommendations that match my taste	reco	**10**	**9**	0.051
Free access	free	11	11	0.041
Possibility to share music tracks outside the music app	share	12	12	0.022
Is used by many of my friends	friends	13	13	0.008

Finally, Table 7 shows the comparison the the outcome attained using count and model approach. Both cases show almost similar ranks for both cases, confirming the statement of Flynn et al. (2013) that the results are independent on the type of the used method.

6.2 Choice of Brand

Best-Worst Scaling approach has allowed to figure out the features in music streaming services which are important in the decision making process of the consumers. In general, the main conclusion which was drawn from the first part of the analysis is that users consider the availability of all the essential artists in the library of the service as the most important factor. However, this attribute is only subjective, as different respondents might find the same service more or less satisfying their preferences. Moreover, the choice of brand may reflect not only their preferences of the service's characteristics, but their lifestyle patterns, or other factors which are not directly linked to brands. In multinomial logit terminology, these parameters are called individual-specific.

Figure 4: Summary by Awareness and Usage

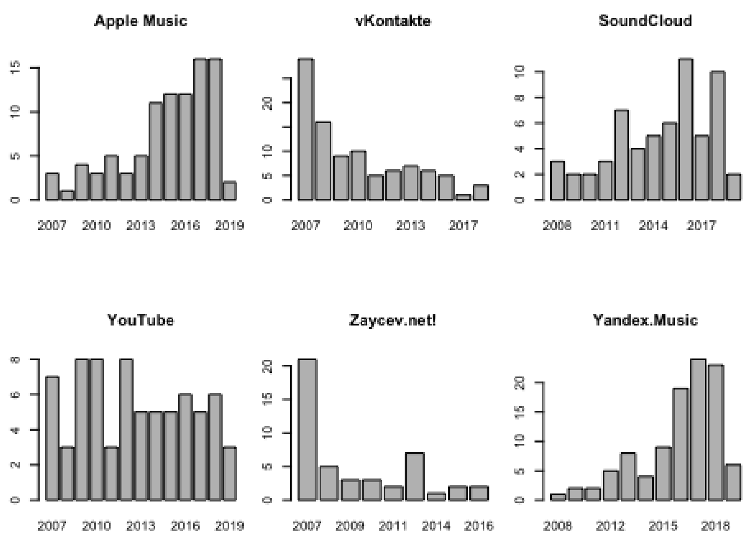


In the survey, respondents were asked about the brands of music streaming services they know at least by name (prompted awareness), services they have ever used, services they used over the last 30 days (proxy for a regular usage) and the brand they consider the main one. The list of brands contained the brands available on Russian market by the launch of the survey. Currently, Russian market is presented by four major brands, i.e. Apple Music, Yandex Music, vKontakte/BOOM and YouTube Music. Brands with minor share of the market, such as SoundClound, Zaycev.net! and Deezer, were also included to make the choice set more complete. Finally, respondents were allowed to add a brand outside the list, which was coded as 'other'. Respondents who chose 'none of above' in any of usage and awareness questions, were excluded from the sample, as they did not match the screening criteria of music services usage. The results regarding usage and awareness can be found on Figure 4. The frequencies are calculated with account for weights.

The graph shows that the knowledge about four biggest brands in Russia is close the the upper limit. Moreover, values for 'ever used' as well as trial usage are only slightly different between Yandex.Music, Apple Music and vKontakte. However, there is a clear distinction in terms of commitment to a brand. The conversion rate between regular usage and main brand is the highest for Apple Music (39/53*100% $\approx$ 74%). In practice, it implies that 3/4 of users who used Apple Music over the last month are committed brand users, while this rate corresponds to half users of Yandex.Music and only a third of vKontakte users. YouTube is trailing behind with only 17 %.

Another statistics providing a clear market picture is the year of the beginning of using the services. Even though it is expected that participants made certain errors naming the exact year they started using the services, Figure 5 gives an idea, whether users subscribed recently or long time ago. In particular, this graph shows that vKontakte and Zaycev.net! acquired most of users in 2007 and started declining significantly since then. On the contrary, Yandex.Music and Apple Music started massively attracting new users after 2015. In other words, around the time when vKontakte started making the steps towards depiratization, users started searching for the alternative services.

Figure 5: Start of Using



Using the basic statistics of usage and awareness, it is possible to make an inference that even though the brands may offer more or less similar feature packages and price plans, they have very different background and represent different values, therefore they attract consumers by other parameters than price. In order to figure out the factors which influence the choice, multinomial logit is used. The dependent variable is the main brand, which is presented in the binary form, where 1 represents that the brand is chosen as the main brand among the alternatives and 0 otherwise. The specification of the model requires the choice set to be mutually exclusive, exhaustive and finite. The analysis focuses the attention on the factors influencing a choice of a particular brand. Option 'other' will not then allow to interpret coefficients, since it is a collective category. Moreover, due to sample limitations, some of the choices present very low frequencies, such as Zaycev.net, Deezer, SoundCloud and YouTube. Thus, is it reasonable to shrink the analysis to an artificially limited choice set, including only Yandex.Music, Apple Music and vKontakte as the main brands of interest.

After filtering users who chose a brand outside of the addressed set, total number of respondents decreased to 130. Due to relatively low sample size, the analysis faces the restriction on the number of independent variables. In such a manner, the first set of regressions concerns only individual-specific characteristics, such as attitude towards music consumption, or lifestyle. In the questionnaire these attributes were revealed through a block of questions, when respondents were asked to evaluate, to what extent they agree or disagree with statements on the scale from 1 to 10, where 1 is associated with 'highly disagree' and 10 is 'highly agree'. Statements, correspondent variables and the summary statistics are presented in Table 8.

Table 8: Lifestyle Descriptive Statistics

Statement	Var	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
I would not pay for music, even if it's affordable	afford	2.400	2.348	1	1	3	10
I listen to music to bring back memories	emot	6.985	2.558	1	6	9	10
I listen to artists that not many people have heard of	excl	5.254	2.479	1	3	7	10
I prefer local brands to the international ones	local	2.854	1.941	1	1	4	10
All my friends pay for the music apps	pay	4.569	2.564	1	2.2	6.8	10
I am among the first of my friends to try new apps	test	4.531	2.921	1	2	7	10

When an individual is making a decision about a brand, she maximizes the utility in accordance with her personal preferences. In case of individual-specific data, the systematic component of the utility for a user n for each of the alternatives is presented in the following manner:

$$V_{n,apple} = afford_n * \gamma_{apple} + ... + test_n * \gamma_{apple} \tag{19}$$

$$V_{n,yandex} = afford_n * \gamma_{yandex} + ... + test_n * \gamma_{yandex} \tag{20}$$

$$V_{n,vk} = 0 \tag{21}$$

where $\boldsymbol{\gamma_j}$ is a vector of alternative-specific coefficients, which have different effect on the outcome for each of the brand alternatives. Since one of the sets of coefficients has to be normalized to zero to avoid identification problem, vKontakte is chosen as a reference option ($\boldsymbol{\gamma_{vk}} = 0$), allowing to interpret the results in relation to this brand. The reason behind lies in the assumption of high conversion level from vKontakte to Apple Music and Yandex.Music, considering decreasing trend of acquiring new users for vKontakte opposed to two other brands. The results of the regression are presented in Table 9.

The first regression shows a full set of individual-specific characteristics, two others are restricted models. Regressions (3) shows very low predictability, with McFadden ρ^2 only 0.036. Apart from McFadden ρ^2, a likelihood ratio test is used, which tests whether a fitted model differs from a null model with zero coefficients. The null hypothesis states that all coefficients for both models are simultaneously equal to zero. In case of regression (3), the null hypothesis is not rejected, unlike regressions (1) and (2) with the hypotheses about zero coefficients are rejected at the .01 significance level. Moreover, McFadden ρ^2 for regressions (1) and (2) show a good fit of the models. As in

Table 9: Multinomial Logit Model (Lifestyle)

	Dependent variable:		
	Brand		
	(1)	(2)	(3)
apple:(intercept)	0.945 (1.223)	1.349* (0.816)	0.422 (0.892)
yandex:(intercept)	0.929 (1.202)	−0.067 (0.833)	1.588* (0.901)
apple:emot	−0.017 (0.120)		−0.012 (0.099)
yandex:emot	−0.142 (0.119)		−0.129 (0.102)
apple:pay	0.382*** (0.148)	0.385*** (0.147)	
yandex:pay	0.318** (0.151)	0.292** (0.149)	
apple:afford	−0.481*** (0.150)	−0.474*** (0.149)	
yandex:afford	−0.204* (0.110)	−0.243** (0.107)	
apple:local	−0.285* (0.158)	−0.280* (0.159)	
yandex:local	0.112 (0.139)	0.108 (0.137)	
apple:test	0.074 (0.116)		0.187* (0.098)
yandex:test	0.095 (0.117)		0.168 (0.105)
apple:excl	0.048 (0.133)		−0.046 (0.107)
yandex:excl	−0.135 (0.130)		−0.174 (0.116)
Observations	130	130	130
McFadden ρ^2	0.196	0.166	0.036
Log Likelihood	−108.019	−112.043	−129.424
LR Test	52.579*** (df = 14)	44.530*** (df = 8)	9.768 (df = 8)

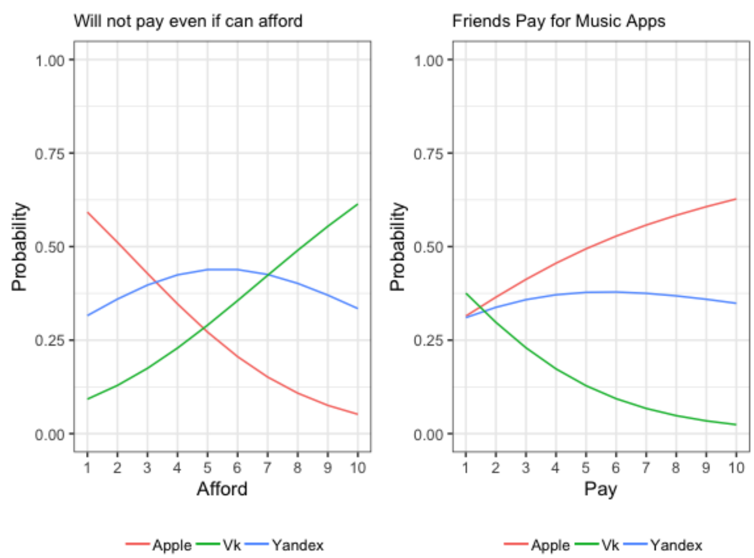
Note: *p<0.1; **p<0.05; ***p<0.01

case of alternative-specific multinomial logit, the coefficients cannot be interpreted directly in their magnitude, but only by their signs. Alternative-specific constants tends to grasp the average effect of all the factors which were not included in the model (Train 2009). Thus, non-zero constants imply that there are factors which reflect propensity of users to choose a brand for other reasons, than those captured in the model.

Overall, the results show that social factor is quite important for users in terms of payment. As it was discussed by Kiriya & Sherstoboeva (2015), one of the sources of the piracy is the social acceptance of the informal practices. Even when users know that streaming and downloading content free of charge is often illegal, they tend to develop these type of attitude, anyway. However, if the norms in the society are changing, it is reflected in behavior on an individual level. In the regression, coefficients for 'all my friends pay for the music apps' are significant at .05 level and have positive sign. It corresponds to the increase in the probability of using Apple Music or Yandex.Music compared to vKontakte which has been exclusively pirate for over a decade.

Attitude towards avoiding paying for content even if it is affordable is another factor which differs Apple Music and Yandex.Music from vKontakte. Coefficients for both brands are significant and have negative sign, which indicates that users who tend to agree with the statement and practically show tendency towards pirating will less likely choose Apple or Yandex and would rather prefer vKontakte. The last significant factor reflects the perception of brands based on their origin. Since Apple music is an international brand, it is less likely to be chosen by people who tend to choose local brands. At the same time, it is logical that Yandex.Music does not differ from vKontakte in this area due to the fact that both brands are Russian. It is worth mentioning, that lifestyle characteristics, such a listening to music to bring back memories, testing new apps and devices or preference of listening to little-known artists do not define preference towards a particular brand.

Figure 6: Predicted Probabilities at the Mean



Even though the magnitude of the coefficients does not have a direct interpretation they can be used for calculating probabilities using the estimated set of parameters. In particular, Figure 6 shows predicted probabilities of different outcomes across all levels of features *afford* and *pay*. In this specification, values of other parameters are assigned to their mean values. In such a manner, the graphs are interpreted in the following manner: as inclination towards rejecting the payment increases, the probability of choosing Apple Music decreases, while probability of choosing vKontakte goes upwards. Yandex.Music does not have a clear tendency, which shows that coefficients of the regression do not reflect the sign of marginal effects. The interpretation of the graph, where *pay* is varying and other variables are fixed at the mean level, is interpreted in a reversed manner. Probability of choosing Apple Music is increasing as more friends pay for music apps, while probability of using vKontakte shows an inverse trend.

Regardless their lifestyle patterns, users also make a decision based on their preferences of different music services' characteristics. In other words, they make a decision about a brand depending on whether or not a certain feature is important to them. Overall, different services vary in their offers. Apple Music does not have a free price plan, which could be a barrier for users who refuse to pay for content. All three brands have different algorithms for music recommendations and automatic creation of playlists. Even the same features can be perceived differently by consumers depending on promotion through marketing campaigns or an individual history of relationships with a brand.

Table 10: Multinomial Logit Model (Features)

	Dependent variable:					
	Brand					
	(1)	(2)	(3)	(4)	(5)	(6)
apple:(intercept)	4.660*** (0.830)	0.178 (0.459)	−0.732 (0.810)	−0.420 (0.777)	0.007 (0.413)	−2.100 (2.234)
yandex:(intercept)	3.849*** (0.828)	−1.566*** (0.585)	0.122 (0.786)	−1.216 (0.848)	−0.323 (0.439)	−4.741** (2.255)
apple:free	−7.098*** (1.269)					−7.755*** (1.578)
yandex:free	−5.704*** (1.205)					−5.782*** (1.538)
apple:reco		1.921* (1.093)				2.934 (1.867)
yandex:reco		4.635*** (1.220)				6.070*** (1.866)
apple:library			2.327** (1.144)			4.200** (2.020)
yandex:library			0.641 (1.144)			2.848 (2.023)
apple:interface				2.612* (1.502)		3.975* (2.393)
yandex:interface				3.402** (1.600)		5.729** (2.357)
apple:share					3.913** (1.592)	5.545** (2.491)
yandex:share					3.818** (1.650)	5.724** (2.550)
Observations	130	130	130	130	130	130
McFadden ρ^2	0.195	0.071	0.016	0.016	0.026	0.326
Log Likelihood	−108.058	−124.833	−132.212	−132.224	−130.812	−90.506
LR Test	52.499*** (df = 4)	18.949*** (df = 4)	4.192 (df = 4)	4.167 (df = 4)	6.991 (df = 4)	87.604*** (df = 12)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 10 shows the results of multinomial logit for variables which represent importance of the features which were used for MaxDiff block. The dependent variable is the main brand used by respondents. In total, 13 features were tested separately to define whether or not they have an impact on a choice of a particular brand. However, only five of them showed significant results, namely free access, music recommendations, availability of all essential artists in the library, user-friendly interface and possibility to share music outside the app. Even though, the latter three items failed the likelihood test in a sense that the null hypothesis that the fitted model has coefficients which are equal to zero simultaneously, these covariates were included in regression (6). The results of this final regression represent the attitude towards different brands with vKontakte as a reference.

As it could be expected from the previous results, coefficients for free access have negative signs for both Apple Music and Yandex.Music, which implies that both brands have lower probabilities to be chosen by people who find free access important and would rather prefer vKontakte instead. Notably, unlike Apple Music, Yandex.Music has a negative sign even though they offer a free price plan and vKontakte has a premium version of the service. Nevertheless, this phenomenon traces back to the perception of brand to be free of charge, as it was nearly 10 years. Other characteristics reflect a higher commitment to Yandex.Music and Apple Music, compared to vKontakte. In particular, Yandex.Music shows better performance than vKontakte in terms of music recommendation, while availability of artists in the library is won by Apple Music. Moreover, users who find user-friendly interface important, are less likely to choose vKontakte as their main brand, as well as those who prefer to share tracks outside the app.

Overall, the multinomial logit analysis has defined five factors which distinguish the brands from each other. However, based on the results from Best-Worst Scaling, on average, users find music recommendations, free access and possibility to share tracks outside the app among the least important. To the contrary, availability of all the essential artists was found the most important characteristic, which represents a brand's competitive advantage. Among the brands which were analyzed, Apple Music is the only brand which has a significant positive coefficient related to this attribute. Thus, it is more likely to be chosen compared to vKontakte, which was assigned to the baseline brand, and has higher odds than Yandex.Music with a zero coefficient.

In the final part of the analysis, the last set of coefficients is used to show the consistency of the users' choice. In the survey, consumers were asked to evaluate the brands they have ever used in terms of matching the characteristics tested in MaxDiff part. Since some of the features are objective and cannot be evaluated on a likert scale, such as free access of lack of advertisement, they were not mentioned in the survey, but coded afterwards. Set of features including high sound quality, user-friendly interface, availability of the essential artists in the library and others, is considered subjective, assuming that different users might have various opinions about the same feature related to the same brand. As the result, an index of satisfaction was calculated, which takes into account, whether a brand is considered preferable in terms of various features, weighted on the importance level of these features:

$$index_{ji} = \sum_{j=1}^{M} Importance_j * match_i \tag{22}$$

where $Importance_j$ is an importance level of a feature from the MaxDiff set of items M and $match_i$ is an indicator variable, with value 1 if a brand was chosen as preferable related to a feature, and 0 otherwise.

The second variable of interest (*likely*) is derived from the question about the likelihood of using a service in the scenario that a new brand which fits the requirements launches the market. Both variables, index and likelihood, have individual values for every respondent for each brand. In accordance with the model specification, the independent variables are alternative-specific, hence they have only one coefficient, independent on a brand. The results of the regression are presented in Table 11.

All three regressions show significant and positive coefficients, as well as very high McFadden ρ^2, which indicates that users are consistent in their choices. Higher index of satisfaction and likelihood of using a brand if a new alternative appears, correspond to a higher probability of choosing a brand.

Table 11: Alternative-Specific Case

	Dependent variable:		
	Brand		
	(1)	(2)	(3)
index	7.194*** (0.970)		4.204*** (1.400)
likely		0.716*** (0.114)	0.507*** (0.112)
Observations	130	130	130
Log Likelihood	−52.638	−33.189	−27.030
McFadden ρ^2	0.631	0.768	0.81
Note:			*p<0.1; **p<0.05; ***p<0.01

To conclude, users in general behave rationally and maximize their utility, choosing a brand which best suits their preferences.

7 Conclusion

This research is raising a question which factors influence consumption preferences in music streaming services market in Russia. Due to complicated institutional background and consumer practice which took the origin in the Perestroika period and developed in the first decade after the collapse of the Soviet Union, any restriction in music or video distribution was perceived as the return of censorship. On a large scale, the market was driven by unwillingness to pay for the content. High demand of Russian internet users for free of charge content resulted in the emergence of one of the biggest sites with pirated music. For almost a decade the leader of the market was a streaming service built into a social network vKontakte, a Russian analogue of Facebook. Only recently vKontakte launched the process of depiratization, forced by the pressure of the international community. As the result, the company has lost its biggest competitive advantage and consequently a big share of committed users who switched to new legal services, such as Apple Music, Yandex.Music and YouTube Music.

The new environment, however, made it unclear, which factors attract users. In particular, one of the mains research objectives was to define how important is the price factor among a set of features offered by different services. Present with the new conditions, will users start searching for alternatives among pirate services to avoid payment or they will adjust their behavior and accept a new proposal? To answer this question, a set of 13 features was tested. Participants of the survey were asked about the most and the least important features of music streaming services, which might potentially influence their decision about a brand. Except for free access and lack of advertisement representing the monetization model, all features reflected non-price characteristics. The second question addressed in the study was focused on the factors which allow users to distinguish brands and make a choice to a greater extent satisfying their preferences.

The research was split into two parts. First, Best-Worst Scaling model has allowed to rank features by their importance. In the second part, multinomial logit model has revealed characteristics of brands' differentiation. The results show, that availability of all the essential artists in the library of the service and offline access are the most important features of consumers' choice. However, the latter does not differ over various brands, which can also be interpreted that this factor has no influence on the choice of the brands, which are currently present in the market. On the other hand, the results suggest that possibility to share music outside the app is a strong differentiating factor. But this characteristic is considered among the least important for a music service. In such a manner, a better performance in terms of availability of all the essential artists combined with high importance of this feature has allowed Apple Music to become the most popular service. These results are indirectly confirmed by a high conversion rate from regular to commitment usage, which is also presented in this study. The biggest surprise of this research is reflected in low importance of free access among other characteristics of music streaming services. From this perspective, the results suggest that the social norms have started to change, and it is oversimplification to consider that the choice of brand is driven exclusively by unwillingness to pay for the content.

However, it is also worth noting limitations of the study, which have an effect on the interpretation of the results. First of all, the sample size is relatively low, which results in high standard errors and consequently poor estimation of probabilities calculated with the obtained coefficients. On the bright side, the the primary goal of the research was to show the direction of the effect, rather than magnitude. Thus, in this study there was no focus on marginal effects, and only signs of the coefficients were interpreted. Second limitation is introduced through the specification of the model. Multinomial logit which is extensively used in the analysis implies that the unobserved portion of consumers' utility is distributed independent and identically. However, in practice this assumption is does not necessarily hold. The brands could exhibit properties which would results in the correlation of the errors, e.g. brands could be split into two nests on the ground of brands' origin, local or international. Further investigation on this issue is required in additional work. Lastly, the sample collection method also causes some concerns. The data was collected via the snowball method, and even though the age range reflects a relatively high level of diversity, there is still a possibility that the sample is not random. Thus, one should be careful applying the results to the entire Russian urban population.

To conclude, the chosen research topic represents a relatively new and fast-moving environment. The market has only recently started to develop and one could expect significant changes in the market size and redistribution of the shares. On the same note, consumers' tastes are also unstable, being influenced by various external factors, such as development of technologies, modifications in the consumer practices, changes in the institutions and social norms, just to name a few. Thus, the results made in this study might be irrelevant already in the near future. However, this study helps to understand the consumers behavior in the current status, forming a baseline for the future research.

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9 Appendix

A. Questionnaire

This survey is a part of my master's thesis research at Stockholm School of Economics.
It will take approximately 5-10 minutes to answer the questions.
Please consider that that no personal data is gathered.
The results will be used only in an aggregated form.
Thank you in advance for your help!
Best regards,
Kseniia

D1. In which country do you reside?

1. Russia
2. Other country

Skip To: End of Survey If D1 = 2

D2. Over the last month (30 days), have you been doing any of the following?

1. Downloaded music for free (1)
2. Purchased MP3 music downloads (2)
3. Listened to streaming music services (3)
4. Watched music videos online (4)
5. Listened to the radio via the Internet (5)
6. None of above (6)

Skip To: End of Survey If D2 != 3

O2. In the next block of questions you will see 13 combinations of different features of music streaming services.
Please, choose what characteristic in each set is the MOST and the LEAST important for you. Consider that some features are used several times.
Press "→"

md1. Which one of the following features is the MOST important for you? Which one is the LEAST important? 1/13

1. Possibility to download a track to the device memory
2. User-friendly interface
3. Possibility to skip unlimited number of tracks
4. Music recommendations that match my taste

md2. Which one of the following features is the MOST important for you? Which one is the LEAST important? 2/13

1. Lack of advertisement
2. Possibility to skip unlimited number of tracks
3. The app works properly/ no crash or bugs
4. All the essential artists are available in the library

md3. Which one of the following features is the MOST important for you? Which one is the LEAST important? 3/13

1. Free access
2. Possibility to download a track to the device memory
3. Wide range of playlists (catalogues by genre, rhythm, occasion, etc.)
4. All the essential artists are available in the library

md4. Which one of the following features is the MOST important for you? Which one is the LEAST important? 4/13

1. Lack of advertisement
2. Offline access
3. Wide range of playlists (catalogues by genre, rhythm, occasion, etc.)
4. Music recommendations that match my taste

md5. Which one of the following features is the MOST important for you? Which one is the LEAST important? 5/13

1. Free access
2. Music recommendations that match my taste
3. The app works properly/ no crash or bugs
4. Is used by many of my friends

md6. Which one of the following features is the MOST important for you? Which one is the LEAST important? 6/13

1. Possibility to share music tracks outside the music app (via social networks, messengers, etc)
2. Music recommendations that match my taste
3. High sound quality
4. All the essential artists are available in the library

md7. Which one of the following features is the MOST important for you? Which one is the LEAST important? 7/13

1. Offline access
2. User-friendly interface
3. All the essential artists are available in the library
4. Is used by many of my friends

md8. Which one of the following features is the MOST important for you? Which one is the LEAST important? 8/13

1. Possibility to share music tracks outside the music app (via social networks, messengers, etc)
2. Wide range of playlists (catalogues by genre, rhythm, occasion, etc.)
3. User-friendly interface
4. The app works properly/ no crash or bugs

md9. Which one of the following features is the MOST important for you? Which one is the LEAST important? 9/13

1. Free access
2. Lack of advertisement
3. User-friendly interface
4. High sound quality

md10. Which one of the following features is the MOST important for you? Which one is the LEAST important? 10/13

1. Wide range of playlists (catalogues by genre, rhythm, occasion, etc.)
2. Possibility to skip unlimited number of tracks
3. High sound quality
4. Is used by many of my friends

md11. Which one of the following features is the MOST important for you? Which one is the LEAST important? 11/13

1. Offline access
2. Possibility to download a track to the device memory
3. High sound quality
4. The app works properly/ no crash or bugs

md12. Which one of the following features is the MOST important for you? Which one is the LEAST important? 12/13

1. Free access
2. Offline access
3. Possibility to share music tracks outside the music app (via social networks, messengers, etc)
4. Possibility to skip unlimited number of tracks

md13. Which one of the following features is the MOST important for you? Which one is the LEAST important? 13/13

1. Lack of advertisement
2. Possibility to download a track to the device memory
3. Possibility to share music tracks outside the music app (via social networks, messengers, etc)
4. Is used by many of my friends

Start of Block: Brand funnel

Q1. Which of the following services for streaming/ downloading music do you know, at least by name?

1. Apple Music
2. BOOM/VK/vKontakte
3. Deezer
4. SoundCloud
5. YouTube/ YouTube Music
6. Zaycev.net!
7. Yandex.Music
8. Other (please specify)
9. Other (please specify)
10. None of above

Skip To: End of Block If Q1 = 10
Carry Forward Selected Choices - Entered Text from "Q1"

Q2. Which of the following services for streaming/ downloading music have you ever used?

1. Apple Music
2. BOOM/VK/vKontakte
3. Deezer
4. SoundCloud
5. YouTube/ YouTube Music
6. Zaycev.net!
7. Yandex.Music

8. Other
9. Other
10. None of above

Skip To: End of Block If Q2 = 10

Q3. Which of the following services for streaming/ downloading music have you used over the last month?

1. Apple Music
2. BOOM/VK/vKontakte
3. Deezer
4. SoundCloud
5. YouTube/ YouTube Music
6. Zaycev.net!
7. Yandex.Music
8. Other
9. Other
10. None of above

Skip To: End of Block If Q3 = 10

Q4. Thinking of the music services which you use regular, out of 10 times, how often would you use each of the following services?
Display This Question: If If Which of the following services for streaming/ downloading music have you used over the last month?
q://Q3/SelectedChoicesCount Is Greater Than 1
Carry Forward Selected Choices from "Q3"

1. Apple Music
2. BOOM/VK/vKontakte
3. Deezer
4. SoundCloud
5. YouTube/ YouTube Music
6. Zaycev.net!
7. Yandex.Music
8. Other
9. Other

Display Total :

Q5. If you had to choose, which one of the following music services you would call 'the main one'?

Display This Question:

If If Which of the following services for streaming/ downloading music have you used over the last month?

q://Q3/SelectedChoicesCount Is Greater Than 1

Carry Forward Displayed Choices from "Q4"

1. Apple Music
2. BOOM/VK/vKontakte
3. Deezer
4. SoundCloud
5. YouTube/ YouTube Music
6. Zaycev.net!
7. Yandex.Music
8. Other
9. Other

End of Block: Brand funnel

Start of Block: Services

Q6. What type of price plan do you currently use for the following music services?

Carry Forward Selected Choices from "Q3"

by row:

1. Apple Music
2. BOOM/VK/vKontakte
3. Deezer
4. SoundCloud
5. YouTube/ YouTube Music
6. Zaycev.net!
7. Yandex.Music
8. Other
9. Other

by column:

1. free
2. premium (paid)
3. free trial of the paid service
4. Hard to say

Q8. Approximately when did you subscribe for these services?
Carry Forward Selected Choices from "Q3"
by row:

1. Apple Music
2. BOOM/VK/vKontakte
3. Deezer
4. SoundCloud
5. YouTube/ YouTube Music
6. Zaycev.net!
7. Yandex.Music
8. Other
9. Other

by column: 2007 ... 2019

Q9. If there is a new service launched and it matches your requirements, how likely will you continue using the following services?
Carry Forward Selected Choices from "Q3"
by row:

1. Apple Music
2. BOOM/VK/vKontakte
3. Deezer
4. SoundCloud
5. YouTube/ YouTube Music
6. Zaycev.net!
7. Yandex.Music
8. Other
9. Other

by column:

1. Definitely will not
2.
3.
4.
5.
6.
7.
8.
9.
10. Definitely will

End of Block: Services
Start of Block: brand satisfaction

Q10.1. Which of the following brands do you find preferable in terms of the following features?
Wide range of playlists (catalogues by genre, rhythm, occasion, etc.) *Carry Forward Selected Choices from "Q2"*

1. Apple Music
2. BOOM/VK/vKontakte
3. Deezer
4. SoundCloud
5. YouTube/ YouTube Music
6. Zaycev.net!
7. Yandex.Music
8. None of above

Q10.2. Which of the following brands do you find preferable in terms of the following features? User-friendly interface
Carry Forward Selected Choices from "Q2"

1. Apple Music
2. BOOM/VK/vKontakte
3. Deezer
4. SoundCloud
5. YouTube/ YouTube Music
6. Zaycev.net!
7. Yandex.Music
8. None of above

Q10.3. Which of the following brands do you find preferable in terms of the following features? Music recommendations that match my taste
Carry Forward Selected Choices from "Q2"

1. Apple Music
2. BOOM/VK/vKontakte
3. Deezer
4. SoundCloud
5. YouTube/ YouTube Music
6. Zaycev.net!
7. Yandex.Music
8. None of above

Q10.4. Which of the following brands do you find preferable in terms of the following features? High sound quality

Carry Forward Selected Choices from "Q2"

1. Apple Music
2. BOOM/VK/vKontakte
3. Deezer
4. SoundCloud
5. YouTube/ YouTube Music
6. Zaycev.net!
7. Yandex.Music
8. None of above

Q10.5. Which of the following brands do you find preferable in terms of the following features? The app works properly/ no crash or bugs

Carry Forward Selected Choices from "Q2"

1. Apple Music
2. BOOM/VK/vKontakte
3. Deezer
4. SoundCloud
5. YouTube/ YouTube Music
6. Zaycev.net!
7. Yandex.Music
8. None of above

Q10.6. Which of the following brands do you find preferable in terms of the following features? All the essential artists are available in the library

Carry Forward Selected Choices from "Q2"

1. Apple Music
2. BOOM/VK/vKontakte
3. Deezer
4. SoundCloud
5. YouTube/ YouTube Music
6. Zaycev.net!
7. Yandex.Music
8. None of above

Q10.7. Which of the following brands do you find preferable in terms of the following features? Is used by many of my friends

Carry Forward Selected Choices from "Q2"

1. Apple Music

2. BOOM/VK/vKontakte
3. Deezer
4. SoundCloud
5. YouTube/ YouTube Music
6. Zaycev.net!
7. Yandex.Music
8. None of above

End of Block: brand satisfaction Start of Block: Lifestyle

Q11. Please indicate to what extent do you agree with each of the following statements?
by row:

1. I prefer local brands to the international ones
2. All my friends pay for the music apps
3. I would not pay for music, even if it's affordable
4. I prefer listening to artists and bands that not many people have heard of
5. I listen to music to bring back memories
6. I am usually among the first of my friends to try new devices and mobile apps

by column:

1. Absolutely disagree
2.
3.
4.
5.
6.
7.
8.
9.
10. Absolutely agree

End of Block: Lifestyle
Start of Block: Demo

D3. To which of the following do you most closely identify?

1. Male
2. Female

D4. How old are you?
18 ... 99

D5. In what city do you reside?

1. Moscow
2. Saint Petersburg
3. Volgograd
4. Voronezh
5. Yekaterinburg
6. Kazan
7. Krasnoyarsk
8. Nizhniy Novgorod
9. Novosibirsk
10. Omsk
11. Perm
12. Rostov-on-Don
13. Samara
14. Ufa
15. Chelyabinsk
16. Other city

Q48. If you have any comments or concerns about this survey, please feel free to leave a note here. Otherwise just skip this question.

End of Block: Demo

B. Correlation Tables

Table 12: Lifestyle Attributes Correlation

	afford	emot	excl	local	pay	test
afford	1.000	0.020	0.022	0.122	**-0.339**	−0.186
emot	0.020	1.000	0.124	−0.050	0.173	0.113
excl	0.022	0.124	1.000	−0.004	0.028	0.401
local	0.122	−0.050	−0.004	1.000	−0.052	−0.061
pay	**-0.339**	0.173	0.028	−0.052	1.000	0.123
test	−0.186	0.113	**0.401**	−0.061	0.123	1.000

Table 13: MaxDiff Features Correlation

	free	adv	offline	download	share	catalogues	interface	skip	reco	sound	bugsf	library	friends
free	1.000	−0.171	−0.036	−0.044	−0.299	−0.160	−0.103	0.070	−0.176	−0.190	−0.138	−0.010	−0.115
adv	−0.171	1.000	−0.256	−0.185	−0.035	−0.080	−0.018	−0.060	0.019	0.041	−0.008	−0.391	−0.071
offline	−0.036	−0.256	1.000	0.414	0.028	−0.383	0.000	−0.170	−0.326	−0.130	−0.134	0.035	−0.103
download	−0.044	−0.185	0.414	1.000	−0.119	−0.243	−0.246	−0.039	−0.394	−0.120	−0.163	0.058	−0.007
share	−0.299	−0.035	0.028	−0.119	1.000	−0.144	−0.011	−0.062	−0.026	0.099	−0.009	−0.242	0.154
catalogues	−0.160	−0.080	−0.383	−0.243	−0.144	1.000	−0.173	−0.098	**0.513**	0.026	−0.202	−0.139	−0.049
interface	−0.103	−0.018	0.000	−0.246	−0.011	−0.173	1.000	−0.193	−0.137	−0.187	0.261	0.079	0.046
skip	0.070	−0.060	−0.170	−0.039	−0.062	−0.098	−0.193	1.000	−0.130	−0.236	−0.053	0.068	0.087
reco	−0.176	0.019	−0.326	**-0.394**	−0.026	**0.513**	−0.137	−0.130	1.000	−0.020	−0.220	−0.113	−0.197
sound	−0.190	0.041	−0.130	−0.120	0.099	0.026	−0.187	−0.236	−0.020	1.000	−0.150	−0.129	0.076
bugsf	−0.138	−0.008	−0.134	−0.163	−0.009	−0.202	0.261	−0.053	−0.220	−0.150	1.000	0.058	−0.087
library	−0.010	−0.391	0.035	0.058	−0.242	−0.139	0.079	0.068	−0.113	−0.129	0.058	1.000	−0.186
friends	−0.115	−0.071	−0.103	−0.007	0.154	−0.049	0.046	0.087	−0.197	0.076	−0.087	−0.186	1.000

C. Awareness and Usage without Weights

Table 14: Awareness of Brands (Q1)

	Brand	Count	Weighted Count	Share	Weighted Share
1	Yandex.Music	152	153.46	96.82	97.74
2	Apple Music	152	151.37	96.82	96.41
3	YouTube/ YouTube Music	138	141.48	87.90	90.12
4	BOOM/VK/vKontakte	138	140.69	87.90	89.61
5	SoundCloud	116	115.24	73.89	73.40
6	Zaycev.net!	109	108.91	69.43	69.37
7	Deezer	48	49.82	30.57	31.73
8	Other_1	49	49.12	31.21	31.29
9	Other_2	18	18.82	11.46	11.99

Table 15: Brands Ever Used (Q2)

	Brand	Count	Weighted Count	Share	Weighted Share
1	Yandex.Music	123	127.05	78.34	80.92
2	Apple Music	111	110.00	70.70	70.06
3	YouTube/ YouTube Music	94	95.03	59.87	60.53
4	BOOM/VK/vKontakte	115	117.44	73.25	74.80
5	SoundCloud	76	76.50	48.41	48.72
6	Zaycev.net!	53	54.58	33.76	34.76
7	Deezer	15	15.90	9.55	10.13
8	Other_1	34	34.06	21.66	21.69
9	Other_2	13	12.64	8.28	8.05

Table 16: Regularly Used Brands (Q3)

	Brand	Count	Weighted Count	Share	Weighted Share
1	Yandex.Music	77	80.72	49.04	51.42
2	Apple Music	85	82.64	54.14	52.64
3	YouTube/ YouTube Music	64	65.81	40.76	41.92
4	BOOM/VK/vKontakte	74	78.09	47.13	49.74
5	SoundCloud	37	38.40	23.57	24.46
6	Zaycev.net!	2	2.55	1.27	1.62
7	Deezer	5	5.47	3.18	3.48
8	Other_1	13	12.72	8.28	8.10
9	Other_2	6	6.00	3.82	3.82

Table 17: The Main Brand (Q5)

	Brand	Count	Weighted Count	Share	Weighted Share
1	Yandex.Music	42	43.30	26.75	27.58
2	Apple Music	63	61.92	40.13	39.44
3	YouTube/ YouTube Music	12	11.63	7.64	7.41
4	BOOM/VK/vKontakte	25	24.94	15.92	15.89
5	Deezer	2	2.47	1.27	1.57
6	SoundCloud	2	1.13	1.27	0.72
7	Spotify	6	6.04	3.82	3.85
8	Google Play Music	3	3.75	1.91	2.39
9	DI.FM	1	1.24	0.64	0.79

D. Multinomial Logit Model without Weights

Table 18: Multinomial Logit Model (Lifestyle)

	Dependent variable:		
	Brand		
	(1)	(2)	(3)
apple:(intercept)	0.872 (1.200)	1.288 (0.802)	0.297 (0.878)
yandex:(intercept)	0.871 (1.200)	−0.117 (0.831)	1.407 (0.892)
apple:emot	−0.020 (0.118)		0.0003 (0.097)
yandex:emot	−0.081 (0.118)		−0.071 (0.101)
apple:pay	0.326** (0.141)	0.328** (0.139)	
yandex:pay	0.275* (0.146)	0.260* (0.143)	
apple:afford	−0.471*** (0.145)	−0.477*** (0.147)	
yandex:afford	−0.234** (0.113)	−0.253** (0.110)	
apple:local	−0.177 (0.153)	−0.166 (0.154)	
yandex:local	0.161 (0.140)	0.152 (0.139)	
apple:test	0.069 (0.113)		0.185* (0.097)
yandex:test	0.048 (0.116)		0.131 (0.105)
apple:excl	0.052 (0.131)		−0.033 (0.108)
yandex:excl	−0.156 (0.130)		−0.185 (0.116)
Observations	130	130	130
McFadden ρ^2	0.184	0.156	0.037
Log Likelihood	−109.559	−113.314	−129.329
LR Test	49.498*** (df = 14)	41.988*** (df = 8)	9.957 (df = 8)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 19: Multinomial Logit Model (Features)

	Dependent variable:					
	Brand					
	(1)	(2)	(3)	(4)	(5)	(6)
apple:(intercept)	4.794*** (0.846)	0.237 (0.458)	−0.583 (0.801)	−0.674 (0.786)	0.119 (0.410)	−1.312 (2.236)
yandex:(intercept)	3.820*** (0.842)	−1.601*** (0.592)	0.069 (0.796)	−1.568* (0.868)	−0.104 (0.434)	−4.104* (2.257)
apple:free	−7.303*** (1.294)					−8.029*** (1.598)
yandex:free	−5.579*** (1.210)					−5.959*** (1.556)
apple:reco		1.806* (1.084)				3.051 (1.885)
yandex:reco		4.609*** (1.220)				6.303*** (1.888)
apple:library			2.184* (1.135)			3.888* (2.008)
yandex:library			0.685 (1.156)			2.554 (2.005)
apple:interface				3.188** (1.544)		3.481 (2.353)
yandex:interface				4.067** (1.656)		5.579** (2.324)
apple:share					3.273** (1.490)	4.696* (2.424)
yandex:share					2.639* (1.562)	4.106* (2.490)
Observations	130	130	130	130	130	130
McFadden ρ^2	0.207	0.074	0.017	0.026	0.021	0.337
Log Likelihood	−106.530	−124.364	−132.014	−130.838	−131.541	−88.987
LR Test	55.557*** (df = 4)	19.888*** (df = 4)	4.589 (df = 4)	6.940 (df = 4)	5.535 (df = 4)	90.642*** (df = 12)
Note:						*p<0.1; **p<0.05; ***p<0.01

E. Multinomial Logit Model

(next page)

Table 20: Features of Streaming Services

	Dependent variable:								
	brand								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
apple:(intercept)	−10.739 (17.364)	1.106** (0.556)	−0.217 (0.673)	1.111* (0.618)	0.839* (0.504)	1.812** (0.753)	0.094 (0.743)	0.135 (0.653)	1.022*** (0.332)
yandex:(intercept)	−28.111 (19.845)	1.091* (0.575)	0.021 (0.688)	1.193* (0.634)	−0.125 (0.558)	1.395* (0.795)	1.328* (0.747)	−0.659 (0.721)	0.946*** (0.346)
apple:free	−6.697** (3.126)								
yandex:free	−2.255 (3.395)								
apple:reco	4.754 (3.057)								
yandex:reco	10.902*** (3.543)								
apple:library	6.007* (3.513)								
yandex:library	5.695 (3.780)								
apple:interface	5.322 (4.263)								
yandex:interface	9.125** (4.469)								
apple:share	6.805* (3.692)								
yandex:share	10.343** (4.192)								
apple:download	0.717 (3.289)			−0.349 (0.996)					
yandex:download	4.522 (3.720)			−1.156 (1.048)					
apple:offline	3.899 (3.238)		1.688* (0.968)						
yandex:offline	5.439 (3.491)		0.828 (1.007)						
apple:bugsf	0.229 (2.987)							1.378 (1.098)	
yandex:bugsf	4.689 (3.471)							2.089* (1.178)	
apple:sound	1.727 (3.451)						1.311 (1.148)		
yandex:sound	1.716 (3.789)						−1.380 (1.223)		
apple:adv	1.422 (2.767)	−0.334 (0.854)							
yandex:adv	2.971 (3.109)	−0.956 (0.907)							
apple:skip	0.065 (3.492)					−1.640 (1.267)			
yandex:skip	2.599 (3.794)					−1.527 (1.344)			
apple:catalogues	−0.250 (3.646)				0.163 (1.005)				
yandex:catalogues	2.988 (4.060)				1.454 (1.059)				
apple:friends									−0.817 (1.645)
yandex:friends									−3.405* (1.977)
Observations	130	130	130	130	130	130	130	130	130
R^2	0.393	0.002	0.009	0.003	0.008	0.004	0.027	0.010	0.011
Log Likelihood	−81.558	−134.050	−133.077	−133.955	−133.231	−133.806	−130.705	−132.989	−132.873
LR Test	105.501*** (df = 26)	0.515 (df = 4)	2.462 (df = 4)	0.707 (df = 4)	2.154 (df = 4)	1.004 (df = 4)	7.206 (df = 4)	2.638 (df = 4)	2.870 (df = 4)
Note:									*p<0.1; **p<0.05; ***p<0.01