The Influence of Users on the Recommendation of New Music through Online-networked Music-streaming Platforms

THESIS

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Rotterdam, June 2017

ABSTRACT

Studies have shown that music directly relates to the part of the brain where decisions are made. This makes the consumer experience of music a top priority for music artists regarding sales. The experience of music is diffused in online music-streaming networks that facilitate new music business model recommendation and peer-to-peer recommendation. This thesis addresses the question of what user characteristics influence the recommendation rate of peer-to-peer recommendation in an online-networked music platform regarding new music. Diffusion in social structures was tested before, but not in an online-networked music platform with real life data of a large population sample. Five hypotheses were formulated to test the research question on data from the online platform Last.fm, extracted through API calls for over 3.000 users. The results show that multiple characteristics can be used as an identifier for influencers in an online-networked platform. It is argued that the characteristics influence the recommendation rate of users. Further research suggested to acquire more data entries in a larger time-span to further strengthen the argument. In conclusion it can be shown that the income for artists may introduce 11.5 times the gain through online-networked social platforms when the identified influencers of a network are targeted in diffusing new music. This is shown in a hypothetical scenario, comparing a random sample of the dataset to a specified sample using the findings of the research.

ACKNOWLEDGEMENTS

I would like to thank my thesis supervisor Arash Yazdiha MSc of the Erasmus school of Economics at the Erasmus University Rotterdam. He always had the time to meet with me, give me feedback and guide me in the right direction whenever he thought it was needed.

I want to thank Jelle van der Waals for helping and steering me through the process of writing an API code. Without his guidance, enthusiasm and persistence, I would not have been able to successfully conduct the data calls.

I would also like to acknowledge the second reader of this thesis. I'm grateful for the time and effort you have put into reviewing this paper.

Finally, I would to thank and express my gratitude to my parents and my girlfriend for giving me the support and encouragement throughout all my years of study at the Rotterdam University, Erasmus University and during the process of writing this thesis. I would not have been able to accomplish this without them. Thank you.

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INTRODUCTION

'Where words fail, music speaks …'

- *H.C. Andersen*

The famous quote of the Danish writer and poet from the 19th century, Hans Christian Andersen, foretold what scientists and academics discovered a millennium later. The majority of decision-making in buying behaviour is made in the part of the brain that is associated with emotions and feelings (Bechara, A. et al, 2000). Pleasurable music directly relates to this part of the brain, making a consumer experiencing music a top priority for music artists (Blood, A. J., & Zatorre, R. J., 2001).

Peers and online business models could diffuse the experience of music in a music-streaming platform that distributes music through online recommendation. Peer to peer recommendations create awareness and generate influence from a fan to his or her network. Business models also recommend music to their users. For example, social music platforms like Spotify and Last.fm present artists to users through 'music recommendation systems' with the purpose of encouraging them to use their platform and listen to the artist's music. Still, peer-to-peer recommendation is shown to be very effective in creating awareness and influencing the market (Trusov, M. et al (2009). Since the rise of music piracy it is hard for upcoming artists to make revenue of selling music online (Granados, N., 2016). Focussing on the creation of awareness and buying intent through influential individuals therefore seems a more profitable approach. But how can individuals with influence in a large network be identified? It may seem logical to conclude that a high amount of followers on music streaming platforms cause for more recommendations and influence in a large network (Freberg, K, et al, 2011). However, it may also be possible that the experience with music creates influence over followers or certain age groups contribute more effectively to music diffusion. Furthermore, a larger network may be more influenced by certain genres compared to small networks.

This study will research what influence the characteristics of users have on the recommendation rate of new music and give insight in how marketing activities of new music could target their market to create product awareness effectively among consumers.

1. RESEARCH OBJECTIVE

New music, whether it is an unknown band or a famous artist's new single, must be distributed amongst the target audience to create awareness. Bands can hire a music distribution or promotion agency, but Word of Mouth or direct recommendation from friends can also have a big influence on awareness (Trusov, M., et al, 2009).

1.1 Problem Statement

Online-networked platforms like Spotify, Last.fm and Itunes are important in the distribution of new music, because it allows users to recommend and send music to their followers. These users advertise for certain artists through Word of Mouth behaviour, but how can the biggest influencers through recommendation be identified?

1.2 Research Question

To answer that question the problem must first be formulated. The problem is formulated as the main question of the paper:

What user characteristics influence the recommendation rate of a user in an online-networked music platform regarding new music?

This paper gives the answer to the problem by doing research. The overall research objective is:

To analyse the relation between the characteristics and recommendation rate of a user in an online-networked music platform.

The overall objective is divided into three specific questions towards answering the problem.

1. What are the online characteristics of users in an online-networked music platform?
2. What is the recommendation rate of users in an online-networked music platform?
3. What is the relation between online user characteristics and the recommendation rate in an online-networked music platform and how is it influenced?

1.3 Definition of Terms

The following terms are used in this paper and therefore defined to clarify their meaning.

1.3.1 Actors

The dictionary definition of the technical term *actors* is "one that takes part in any affair" (Merriam-Webster, 2017). In this paper, the term *actor* is used to mean "a person who can be an influencer or follower in a socially networked structure" as used by Jacqueline J. Brown and Peter H. Reingen (1987) in their study on social ties and referral behaviour.

1.3.2 New music

In this paper, the technical term *new music* is used to mean “a single, album, EP or artist that is released in 2017”.

1.3.3 Online-networked platform

In this paper, the technical term *online-networked platform* is used to mean “an online platform, where people can communicate, interact and become friends with each other to create an online community”.

1.3.4 Social Structures

The dictionary definition of the technical term *social structure* is “the internal institutionalized relationships built up by persons living within a group (such as a family or community) especially with regard to the hierarchical organization of status and to the rules and principles regulating behaviour” (Merriam-Webster, 2017). In this paper, *social structures* are used to mean “internal relationships built up by individuals, forming groups in online communities” as used by R.S. Burt in his study on structure holes.

1.3.5 Structure holes

The technical concept of *structure holes* was developed by R.S. Burt and is used in this paper to mean “the gap between two individuals that have complementary sources of information”. It defines the parts between social groups that have to be bridged by individuals to diffuse information to other social groups.

1.3.6 User

The dictionary definition of the technical term *user* is “one that uses” (Merriam-Webster, 2017). In this paper, the term *user* is used to mean “a person on an online-networked platform that can communicate, interact and become friends with other users in the network as used by H. Bisgin et al (2010) in his study on homophily in online social networks.

2. RELATED LITERATURE & FRAMEWORK

The related literature features the theoretical paradigm and the conceptual framework. First the theoretical paradigm regarding the thesis topic is examined on an academic and managerial level and finally the framework regarding the research made.

2.1 Academic Literature

2.1.1 Effects of Word-of-Mouth versus Traditional Marketing
It is important to address the definition of Word-of-Mouth (WOM) marketing and what this behaviour means in this paper. Studies over the years gave WOM a lot of different definitions. From a driving force behind product awareness (Ryan & Gross, 1943) to an 'organic inter-consumer influence' (Kozinets, et al, 2010, p.72). However, all definitions describe information passing from one person to another as a form of recommendation, knowingly, as well as unknowingly.

Michael Trusov, Randolph E. Bucklin and Koen Pauwels (2009) studied the effect of WOM/recommendation compared to traditional marketing. Their findings were that WOM had a significantly longer carry-over effect and higher long-run elasticity compared to marketing events and media appearances. They argue that peer-to-peer recommendation can therefore be an important influencer in addition to other marketing methods.

This can be related to the recommendation of new music in online-networked social networks. Recommending music to another user on an online platform is a form of digital WOM behaviour that can reach further then communicating with one person. Listening to music that is displayed on the online-networked platform is WOM behaviour that can influence the users entire network.

2.1.2 The Strength of weak ties
The digital WOM behaviour can be vital in diffusing new music on an online-networked platform. WOM in a small network can be related to huge macro level awareness according to Mark S. Granovetter (1973). He studied strong and weak ties in networks regarding information diffusion, focussing on the weak ties within groups and the relevance of those connections. He provided a promising explanation of how WOM on a micro level is related to macro level awareness. A user in an online-networked platform can intentionally or unintentionally recommend new songs to strong ties (close real-life friends) and weak ties (never spoken followers). Other studies on consumer behaviour focus on communication through only strong ties (Arndt 1967; Leonard-Barton 1985), because strong ties are easily motivated to share information or resources and circulate it through the platform (Granovetter, 1982). However, Granovetter stated that weak ties are vital in clarifying and explaining a variety of social phenomena. Jacqueline J. Brown and Peter H. Reingen (1987) elaborated on this and stated that in WOM and referral behaviour "the strength of weak ties" arises as a bridging function that allows information to go from a densely knit social structure of referral actors to a more cohesive segment of the broader referral system (Brown, J.J. & Reingen, P.H., 1987, p. 352).

R.S. Burt (2004) interpreted the importance of weak ties in his research on structure holes and good ideas, where he argued that people within a social group have more homogeneous opinions and behaviour than between groups. People on the edge of social groups are supposed to be near a social structure hole, causing them to be more familiar with alternative ways of thinking and behaving. Actors can influence an online-networked platform with new music and audibly appeal to strong and weak ties. According to R.S. Burt (2004), real-life friends will homogeneously respond within the social group. The weak ties are on the edge of the social group and can therefore have a different positive reaction to the new music. These ties then form the catalyst of recommendation towards other networks within the platform. This is where Burt considers the importance of bridging ties towards diffusion, whereas Granovetter favours the consideration of the strength of ties to determine diffusion. The importance of weak ties according to Granovetter is illustrated in Figure 1 and creates the foundation of diffusion in online-networked platforms.

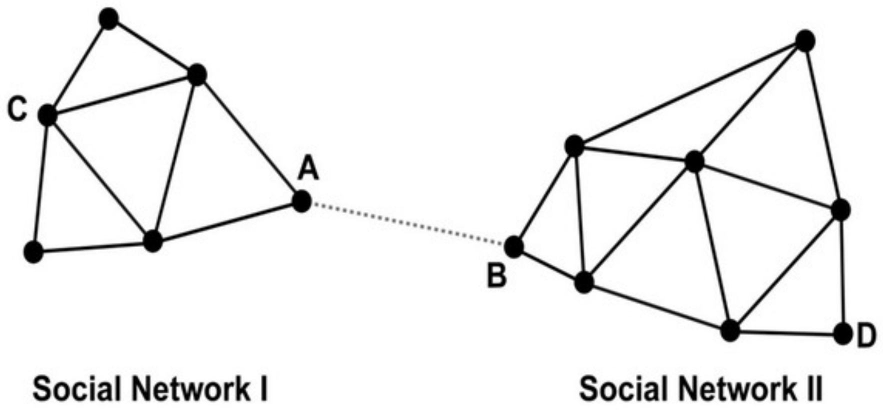


Figure 1: Granovetter's Weak Ties Theory (Adapted from: Granovetter, M.S. (1973), "The Strength of weak ties," American Journal of sociology, vol. 78, Issue 6(May 1973), 1360 – 1380)

2.1.3 The Role of Social Hubs

J. Goldenberg focussed on the importance of individuals with a large number of ties, namely hubs, regarding the diffusion and adoption process in a networked platform. Trusov, et al (2009) examined an online social network and found that an individual is influenced by a few people, but also influences a few people. They also found strong heterogeneity among users regarding their influence on others. Although this was not focussed on the adoption process of a network, it may still imply that hubs are important, according to Goldenberg (Goldenberg J. et al, 2009, p. 3).

Goldenberg stated that there are two kinds of hubs regarding general adopter categories, namely hubs with early adopters and hubs with the main market and laggards. He named them innovative hubs and follower hubs respectively. His findings were that hubs tend to adopt earlier in the diffusion process of a social network, even though they are not necessarily innovative. Also follower hubs have a bigger impact on the total amount of adoptions and the innovative hubs have a larger impact on the speed of the adoption process. Furthermore he found that a small sample of hubs offers great success against predicted failure early in the diffusion process. This implies that new music can be diffused faster with a small sample of innovative hubs, carrying over the music to the follower hubs.

2.1.4 Homophily among social networks

A user in an online-networked platform can intentionally or unintentionally influence his or her followers. When influence is intentional, the user is aware of the recommendation towards certain followers and seeks to create more awareness. When influence is unintentional, the user is unaware of the recommendation towards followers and may have been composed from homophily, the act of connections creating similarity. Homophily can also be caused by exposure outside the network, for example music marketing efforts and traditional WOM. Figure 2 below gives a schematic overview of two ways homophily can influence social structures.

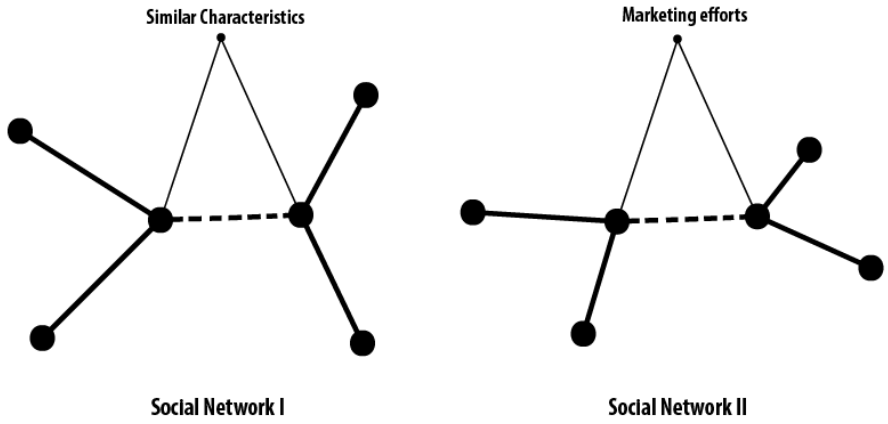


Figure 2: Schematic visualization of two ways homophily can influence networks

Bisgin, Agarwal and Xu (2010) studied the concept of homophily in online social networks and found that social structures have very similar interests to each other and the entire network population. This implies that the social structures do not have distinctive interests, indicating that the ties in those communities are not governed by homophily. However, this research does not cover an earlier research by N.K. Baym and A. Ledbetter (2009) on friendship prediction in music-based social networks. Their findings were that common interests in social structures do not develop strong ties, but do develop weak ties. As stated and cited earlier, the weak ties are vital in the social network diffusion across multiple communities because of their bridging function between these social structures (Granovetter, M.S., 1973; Burt, R.S., 2004; Brown, J.J. & Reingen, P.H., 1987).

2.1.5 Six Degrees of Separation

To study the population of a networked platform, the measurement of the population sample must be credited to present a credible study. Stanley Milgram (1967) experimented on how far people would be away from each other in his research, "The Small world problem". His findings were that everybody in the world is connected to each other through a maximum of six steps of people known. If information were given to a person, it would arrive at the destination anywhere in the world within six steps of intermediaries. This finding Milgram later called the six degrees of separation. According to Milgram's study (1967), a research that uses the user's friends six times will create a representable population of the online-networked platform.

2.2 Managerial Literature

2.2.1 Market orientation

Marketers of music labels or independent music bands can influence a specific group of consumers through targeting to gain more effective results. This is also called market orientation and the effect was stated as profitable for decades before J.C. Narver and S.F. Slater (1990) proved it with their research on the effect of market orientation on profitability. This means that information and demographics about a potential consumer group are vital in orienting the market and targeting the right consumers. In an online-networked music-streaming environment it can be proposed that nationality is an interesting demographic to take into account and research, because of the diverse effect social and cultural diversity can have as stated by R.J. Crisp & R.N. Turner (2011).

E. Sivadas, et al (1998) elaborated on the application of targeting in online environments. They stated that the Internet facilitates identification and access to very narrow segments of consumers. Within product categories the demographics of consumers are tools to segment the population, but Sivadas stated that with Internet access the consumer behaviour and preference also plays a large role in segmenting the population. With segmenting online-networked streaming platforms the user behaviour, such as the song count and genre preference, is vital in segmenting the population in target groups.

2.2.2 Online-networked social platform income and facilitation

Last.fm is an online-networked social music-streaming platform that will be used as an income and facilitation reference for other platforms. The online platform facilitates music streams for over 280.000 labels and artists with around 60 million active accounts (CBS Interactive, 2013; Blog.Last.fm, 2009). Over 43.6 million accounts are subscribed to the music-streaming service for $36 a year, $3 per month (Last FM, 2013).

Since 2014 signed artists as well as independent artists are free to enter their music on last.fm. For every play they receive $0,001, an average across webcasting rates (CDM, 2008). This means that the track ‘Rolling in the Deep’ by ‘Adele’ has generated $1.181 since release, whereas her album ‘21’ generated $6.823 since 2011. Although the rates are transparent and go to straight to the artist, the revenue is not high for a renowned artist. An online-networked platform like Last.fm is therefore more valuable as a source for diffusing and recommendation of music to encourage mp3 downloads, CD sales and concert ticket sales. A research by music metric (2013) showed that Last.fm converts more album sales compared to Facebook and Twitter. This indicates that a large social media fan base and buzz does not guarantee high album sales. Figure 3 shows a snapshot of last.fm on an artist’s page, showing active promotion towards buying the album.

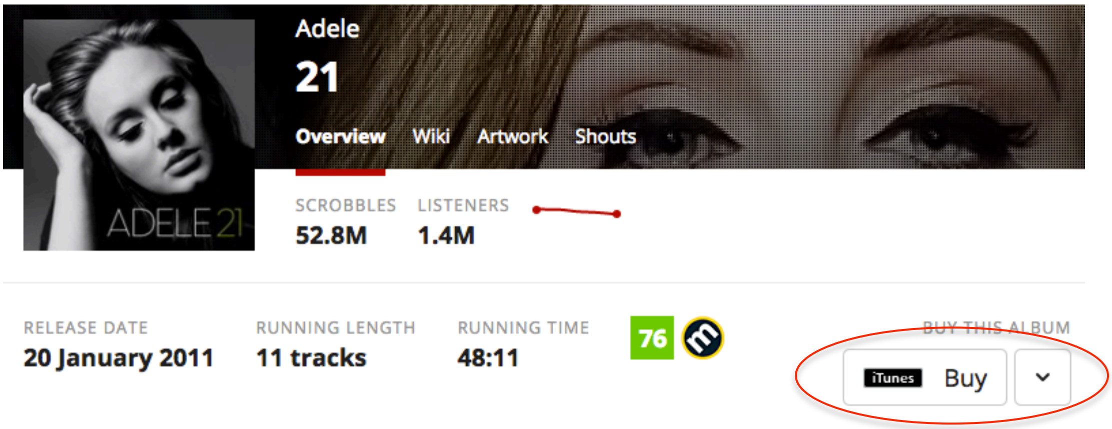


Figure 3: Snapshot of an artist's album last.fm page. Copyright 2017 by CBS Interactive, reprinted.

Assuming an average online conversion of 4% for E-commerce (SmartInsights, 2017), the generated album sales with 1.4 million listeners are 56.000 albums times $13. The main purpose for artists on an online-networked social platform could therefore be creating traffic towards the artist and song page to encourage album sales.

Last.fm facilitates two ways of music recommendation. The first method uses algorithms of the website to recommend music that is similar to previously played music. The listen behaviour of a user is tracked and music of similar artists is presented on the home page and profile page of a user. Figure 4 shows an example of music recommendation through the websites algorithms.

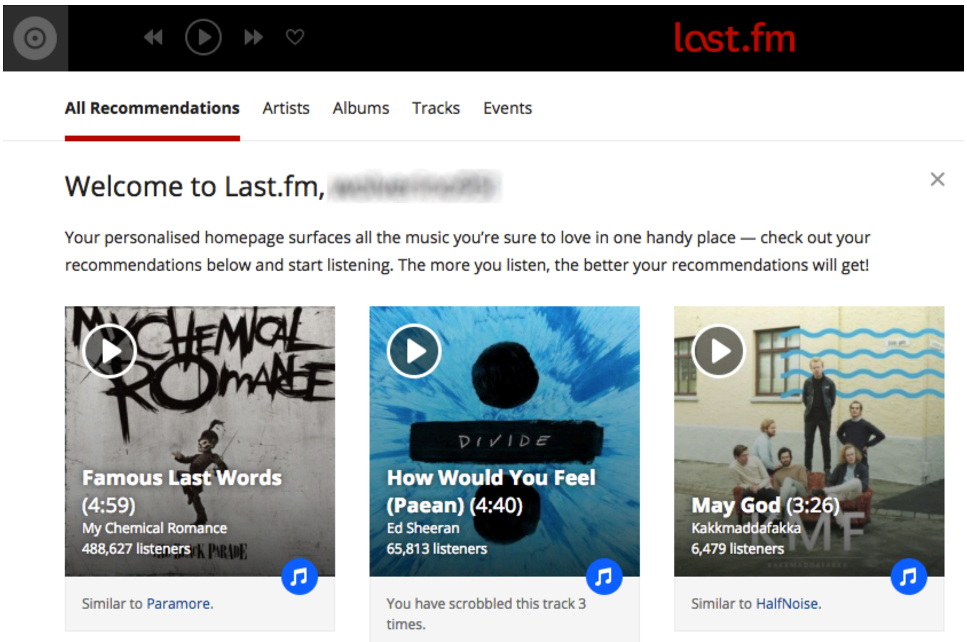


Figure 4: Snapshot of a user last.fm page. Copyright 2017 by CBS Interactive, reprinted.

The second method to facilitate music recommendation uses the listening behaviour of the user's friends to recommend music that is liked by their network. Users can influence others in their network by listening to music or by sending a direct message to a follower to listen to a song. Figure 5 shows an example of user recommendation through network listening behaviour.

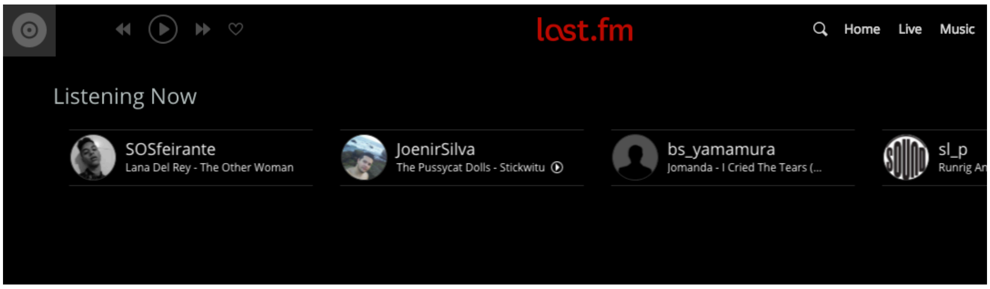


Figure 5: Snapshot of a network live feed of network played songs on last.fm. Copyright 2017 by CBS Interactive, reprinted.

The methods of recommendation can lead to increased traffic to the artist and song pages. Traffic can be converted to album sales through Itunes, Amazon or e-Bay purchases.

2.3 Conceptual Framework

The theoretical paradigm described that influencers with a large number of strong and weak ties in an innovative hub can have a big impact on the diffusion and adoption process of new music in an online-networked music platform. It also showed that market orientation is vital for effective marketing success and WOM important in creating awareness for artists as well as the platforms. This research seeks to find possible demographics and behaviour of influencers among early adopters with higher diffusion and adoption rates. The aim is to predict what type of users should be targeted to effectively diffuse new music in an online-networked platform.

The main question of this paper states:

What user characteristics influence the recommendation rate of a user in an online-networked music platform regarding new music?

2.4 Hypotheses

A.C. North, D.J. Hargreaves and S.A. O'Neill (2000) studied the importance of music among 13 to 14 year old adolescents in England. They found that music is a major aspect in the lives of most young people, on a social, emotional and cognitive level. On an online-networked platform certain age groups will cluster and form online-networked social structures according to R.S. Burt's homogeneity in social structuring across networks (2004). The high density and involvement of adolescent age groups are proposed to have a positive effect on the recommendation rate in comparison with younger and older age groups, as follows:

H1: Age groups between 14 and 20 years old have a higher recommendation rate regarding new music towards followers.

Studies have shown that increased work and time spent on a subject increases influencer's credibility towards followers regarding that subject (Wiedmann, K. P, 2007; Freberg, K, et al, 2011). A study by M. López and M. Sicilia (2014) showed that a higher credibility of a recommendation source positively influences decision-making. The study therefore suggests that users who listen to music more often are likely to have a bigger influence on decision-making towards their followers. It can be proposed that higher song play counts have a positive effect on the recommendation rate regarding new music, as follows:

H2: Users who listened to more songs have a higher recommendation rate regarding new music towards followers.

Similar to the increased work and time spent on a subject, high levels of followers make users appear more credible in giving recommendations towards their followers (Freberg, K, et al, 2011; López, M., & Sicilia, M., 2014). Moreover, R.S. Burt (1999) argued that opinion leaders in social structures are more like opinion brokers, having connections across multiple networks to act as a catalyst for information from one network to another. A high friend count can be considered more likely to have followers in multiple networks, so it can be proposed that a higher friend count has a positive effect on the recommendation rate regarding new music, as follows:

H3: Users with a higher friend count have a higher recommendation rate regarding new music towards followers.

R.J. Crisp & R.N. Turner's (2011) research shows that experiences of social and cultural diversity diverse in outcome. When the experience involves social or cultural conflicting frames it tends to cause stress or marginalization of the desired effect. However, if the social or cultural conflicting frame is integrated, the experience can lead to cognitive flexibility towards the desired effect. It can be proposed that the social and cultural frame of the U.S. and Europe are integrated more with present popular music due to the origin of most artists in western culture. The companies of online platforms are also from western countries like Sweden (Spotify) and the United Kingdom (Last.fm). There originates the community, so it could be assumed more users are actively involved in the U.S. and Europe compared to other countries. Therefore the hypothesis states:

H4: Users with a nationality from the U.S. or Europe have a higher recommendation rate in the relation between the characteristics and recommendation rate of a user regarding new music.

An earlier study by A.C. North and D.J. Hargreaves (1995) on music genres and popularity states that liking music and familiarity have a positive relationship and that liking and music complexity have a more difficult relation. Moreover, P. Tagg (1982) stated that popular music is considered middle-of-the-road pop and rock, with a heterogeneous target audience. It is therefore proposed that the modern popular music genres pop and rock have a positive effect on the association between the characteristics and recommendation rate of a user regarding new music, because these genres have a considerable pleasant hedonic tone and are familiar with a large target audience in multiple social structures. The hypothesis states:

H5: The music genre pop and rock have a higher recommendation rate in the relation between the characteristics and recommendation rate of a user regarding new music.

To identify the characteristics of large influencers a set of characteristics will be compared to the recommendation rate of a user and tested with the hypotheses to see if there is an association between the characteristics of users and the diffusion in an online-networked platform. Table 1.1 shows the hypotheses and their supporting literature.

Hypothesis	Literature support
H1: Age groups between 14 and 20 years old have a higher recommendation rate regarding new music towards followers.	A.C. North, D.J. Hargreaves & S.A. O'Neill (2000) R.S. Burt (2004)
H2: Users who listened to more songs have a higher recommendation rate regarding new music towards followers.	K.P. Wiedmann (2007) K. Freberg, et al (2011) M. López & M. Sicilia (2014)
H3: Users with a higher friend count have a higher recommendation rate regarding new music towards followers.	K. Freberg, et al (2011) M. López & M. Sicilia (2014) R.S. Burt (1999)
H4: Users with a nationality from the U.S. or Europe have a higher recommendation rate in the relation between the characteristics and recommendation rate of a user regarding new music.	R.J. Crisp & R.N. Turner's (2011)
H5: The music genre pop and rock have a higher recommendation rate in the relation between the characteristics and recommendation rate of a user regarding new music	A.C. North, D.J. Hargreaves (1995) P. Tagg (1982)

Table 1.1: Hypotheses and the supporting literature

2.5 Independent Variables

The independent variables of this research describe the characteristics of a user in an online network and consist of user age, song play count and friend count.

2.5.1 User age
The age of a user is used as an independent variable to determine whether certain age groups have a positive effect on the recommendation rate in an online-networked platform.

2.5.2 User song play count
The total amount of songs played is an independent variable to determine whether users with more listening experience have a positive effect on the recommendation rate of users in online-networked platforms.

2.5.3 User friend count
The amount of followers of the user is an independent variable to determine whether the amount of followers has a positive effect on the recommendation rate of a user in online-networked platforms.

2.6 Dependent Variable

The dependent variable will be the amount of times a user, knowingly or unknowingly, recommends new music to his or her friends on the online-networked platform. This is called the recommendation rate.

2.6.1 Recommendation rate

The recommendation rate is the amount of times a friend of a user listens to intentionally or unintentionally recommended new music divided by the amount of recent tracks a user listened to. This is the dependent variable to determine what characteristics have a positive effect on the recommendation rate.

The recommendation rate in this research is interpreted as intentional and unintentional recommendations through the online-networked platform, but also as intentional and unintentional recommendations through associations and bonds outside of the online-networked platform, for example through real life conversations, media outlets or similar interests and lifestyles. The homophily of the population in an online-networked platform can be used to explain registered recommendations between users even if there is no intentional recommendation made online.

2.7 Moderator Variables

The interaction variables are used in the framework to see if they have any effect on the strength of the possible relation between the characteristics and the recommendation rate of a user in an online-networked platform.

2.7.1 User nationality

The nationality of a user is a moderator variable to determine how it affects the relation between the characteristics and recommendation rate of users in an online-networked platform.

2.7.2 Music genre

The music genre a user listens to the most is the moderator variable to determine how it affects the possible relation between the characteristics and recommendation rate of a user.

All variables are collected from users like the data entry as shown in table 1.2 below.

Username	Age	Nationality	Play count	Friend count	Genre	Recommendation rate
miumomo	31	Germany	54358	147	Electronic	5,33%

Table 1.2: Sample data collection of the variables

The framework below schematically visualizes the conceptual framework of this study in a concept map.

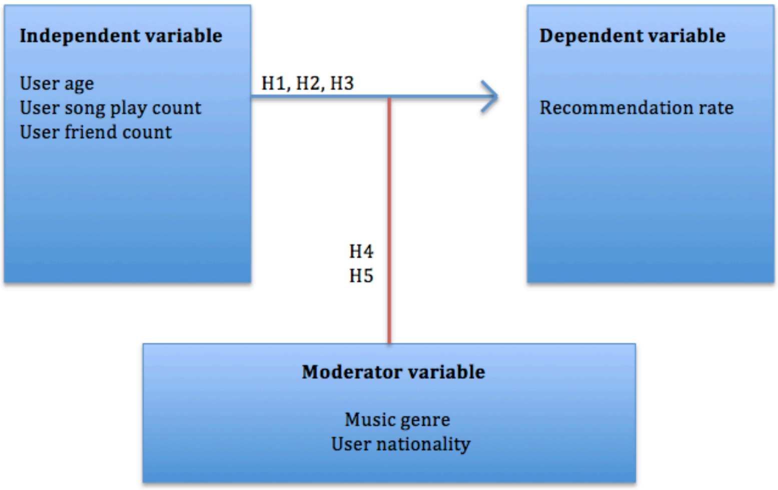


Figure 6: Schematic visualization of this study's conceptual framework

2.8 Data Collection

The hypotheses must be tested with a sample size that represents the entire population of an online-networked platform. To capture the connections of social structures on the platform, the 6 degrees of separation theory by Stanley Milgram (1967) will be applied. This can also be called a snowball effect, where it starts with one user and with the respondents friend list the next set of users is chosen (Kooiker, R., M. et al, 2011, p. 154).

The chain referral sampling suffers criticism regarding verifying and controlling the respondents during the experiment (Biernacki, P., & Waldorf, D., 1981). This method will be used and viable in this research, because the problems of verification and control are rectified with the absence of interaction with respondents and the online collection of data on an online platform that is relevant for this study.

When a user in an online-networked platform is registered, his friend list will be the next list of users that is registered. This is repeated six times to represent the population of an online-networked platform according to the 6 degrees of separation theory. The population sample then amounts around 3.000 users from all over the world. According to the formula of calculating sample size the minimum size of a sample, for a total population of 20.000 or more, should be 385 respondents when a confidence level of 95% and a margin of error of 5% is considered (Raosoft, Inc., 2004). The use of secondary data allows for huge datasets and a very high confidence level.

2.9 Data and Assumptions

The data was collected from the online-networked platform called Last.fm. This online streaming platform has a population of almost 60 million active accounts and allows API calling to gather and use data for application purposes (CBS Interactive, 2013). The API calls include all of the variables that are proposed for this research. Therefore, it provides the optimal environment for gathering the characteristics and recommendation data of users in an online-networked music environment. Furthermore, other streaming platforms are able to link the listening behaviour of users to Last.fm. This is called 'scrobbling' and allows Last.fm to have listening behaviour data from multiple platforms.

The collection of the sample data was put in Word Excel. The data was then transferred to SPSS to test for validity and normality.

2.9.1 Frequencies
The first exploratory tests showed the mean results of the variables and general frequencies of the dataset. The mean value for the song play count of users is 63.648 songs with a standard deviation of 120.071, median of 33.780 and mode of zero. The high standard deviation indicates a wide spread of values across the user song play count and the mode indicates that users with exactly the same amount of song counts have listened the most to zero songs.

The mean value for friend count is 276 followers, with a standard deviation of 1119, median of 47 and mode of 1. The high standard deviation indicates a wide spread of values across the friend count and the mode indicates that users with exactly the same amount of friends have one friend the most. Table 1.3 below shows the modification data of the user song play count and the friend count.

Statistics

		User song play count	User friend count
N	Valid	3144	3144
	Missing	0	0
Mean		63647,14	275,42
Median		33780,50	47,00
Mode		0	1
Std. Deviation		120071,801	1118,955

Table 1.3: Modification values user song play count and friend count

The recommendation rate of the data has a mean value of 0,6%, with a standard deviation of 2,07, median of zero and a mode of zero. The median and mode indicate that most users have no recommendation rate towards followers. Table 1.4 shows the data frequencies of the recommendation rate.

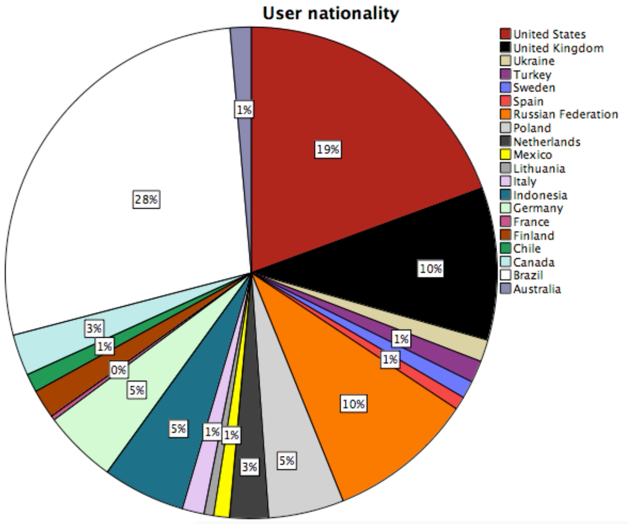
Statistics

Recommendation rate

N	Valid	3144
	Missing	0
Mean		,5953
Median		,0000
Mode		,00
Std. Deviation		2,07698

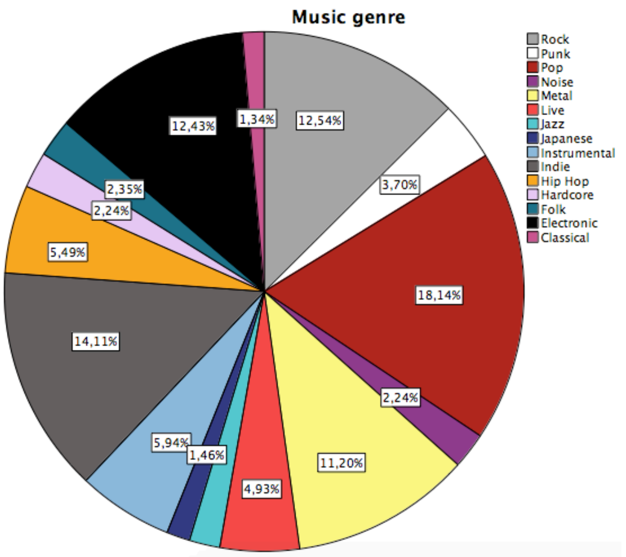
Table 1.4: Modification values recommendation rate

The nationality was excluded when there was a frequency of 4 or less. The used nationalities are assembled in frequency table 1 of appendix D and schematically visualized in pie graph 1.1. The mode of nationality is Brazil with 28% and the United States follows with 19%.



Graph 1.1: User nationality pie graph

The music genre was excluded when there was a frequency of 9 or less. The music genres are shown in frequency table 2 of appendix D and are schematically visualized in pie graph 1.2. The music genre mode is pop with 18,14%, followed by indie (14,11%) and rock (12,54%) music.



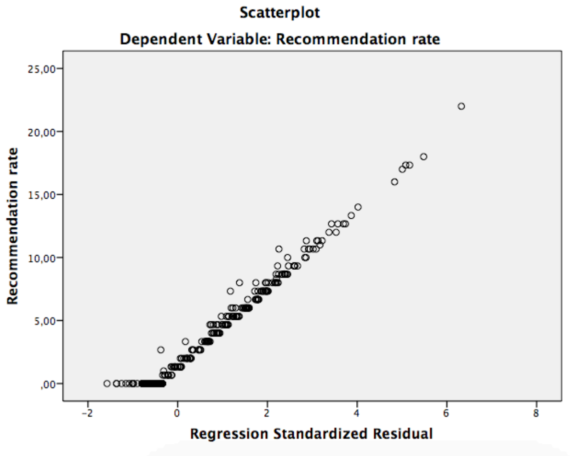
Graph 1.2: Music genre pie graph

2.9.2 Assumptions

The data should meet certain assumptions to be able to perform linear regression analyses that aren't skewed or biased. There are four general assumptions for linear regression analyses as described in the SPSS statistics textbook by Alphons de Vocht (2012).

- The assumption of linearity
- The assumption of multivariate normality
- The assumption of independence of observations (includes auto-correlation -> Durbin-Watson)
- The assumption of homoscedasticity

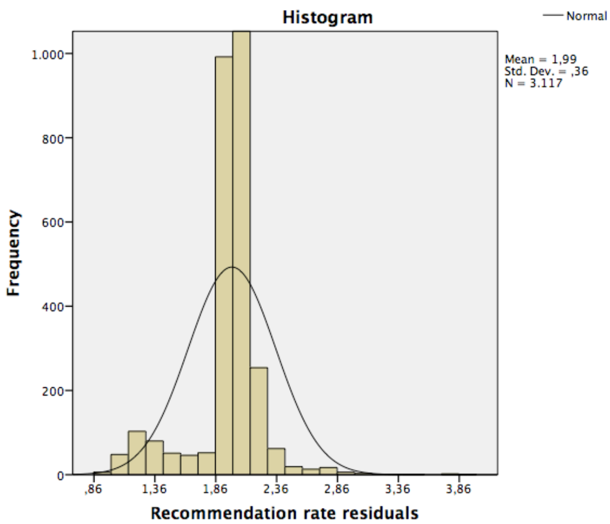
The first assumption was tested with data outlier tests and linearity tests of the standardized residuals. The data outliers were excluded with the Malhalanobis function for every variable. The function generated a value for every data point and a filter excluded the variables below 0,001. After excluding the outliers a scatterplot was made with the dependent variable on the Y-axis and the standardized residuals on the X-axis and is shown in Graph 1.3 below.



Graph 1.3: Recommendation rate scatterplot for linearity

The scatterplot indicated the relation between the dependent and independent variable is linear and therefore the first assumption of linearity is met.

The second assumption was tested by looking at the normal distribution of the residuals and the residual plot shown in graph 1.3. The residuals were saved and depicted in a frequency table to test for normality as shown in graph 1.4 below after outliers were excluded with the mahalanobis test.



Graph 1.4: Residuals of the recommendation rate histogram

The histogram is skewed to the right, but it is not heavily deviated from a normal distribution. The table 1.5 and 1.6 below show that the dependent variable is not considered normal according to the normality tests kolmogorov-Smirnov and Shapiro-Wilk.

Descriptives

			Statistic	Std. Error
Recommendation rate residuals	Mean		1,99	,006
	95% Confidence Interval for Mean	Lower Bound	1,98	
		Upper Bound	2,01	
	5% Trimmed Mean		2,00	
	Median		2,01	
	Variance		,130	
	Std. Deviation		,360	
	Minimum		1	
	Maximum		8	
	Range		7	
	Interquartile Range		0	
	Skewness		4,330	,044
	Kurtosis		57,716	,088

Table 1.5: Normality tests descriptive of the dependent variable

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Recommendation rate residuals	,356	3117	,000	,564	3117	,000

a. Lilliefors Significance Correction

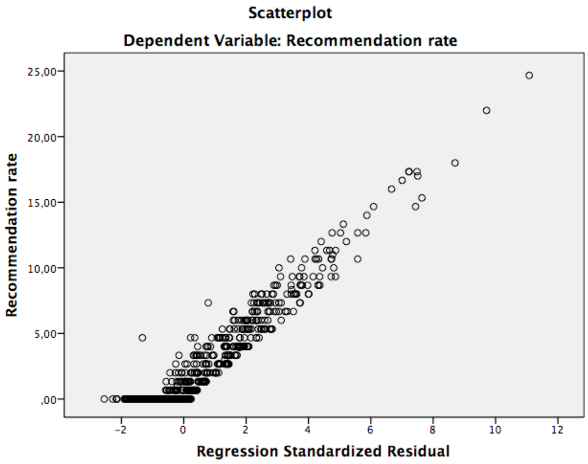
Table 1.6: Normality tests of the dependent variable

These tests are very specific however, and often cause large life tested datasets to be non-normally distributed. When the residual plot of graph 1.3 is examined instead, a strong linear relation between the independent and dependent variable can be seen. Therefore the second assumption of multivariate normality will be validated.

The residual plot of graph 1.3 also shows a strong linear relation between the independent and dependent variable. Therefore it can be said that the second assumption of multivariate normality is met.

The third assumption was tested by excluding all data entries that recorded a user multiple times and by examining the Durbin-Watson value for auto-correlation. Before the cross-sectional dataset was entered into SPSS the excel list was screened on duplicates to avoid multiple observations of the same data. Furthermore, the Durbin-Watson value was used in all regression analyses to test for auto-correlation. All values were between 1,5 and 2,5, with a value of 2 meaning no correlation, as shown in table 2.1 to 2.3, 3.1 to 3.3, 4.1 to 4.6 and 5.1 to 5.6 in appendix D. Therefore it can be said that the third assumption of independence of observations was met.

To test the final assumption all independent variables were plotted with the dependent variable. The goal was to see if it had a linear relation and data entries that didn't fan out in a triangular fashion. The scatterplot of the dependent variable with the independent variables is shown in graph 1.5 below.



Graph 1.5: Recommendation rate scatterplot for homoscedasticity

3. METHODOLOGY

In this chapter the research design and -methods are discussed. It uses the literature as a foundation and explains why certain methods are used, as well as the academic basis of those choices.

3.1 Research Design

This study aims to give insight about how actors influence other people in an online-networked music platform and is dedicated to provide new information for the literature of social sciences. Therefore, this study is a fundamental research (Kooiker, R., M. et al, 2011, p. 16).

To collect data about recommendations of new music in online-networked platforms a large dataset of recent activity must be gathered, together with characteristics of influencing actors. The data must be collected from a set of respondents in an online-networked platform from all over the world. This can only be done through observation and registration of quantitative data in the environment of an online platform (Kooiker, R., M. et al, 2011, p. 174).

3.2 Participants

The population sample that will be examined in this research will be acquired non-randomly. The respondents will be recruited with the friend lists of previous respondents. This causes the selection to be non-random, because there will be some selection to the process where some individuals are in a friend list and others aren't.

3.2.1 Protection of Human Subjects

By analysing the population of an online-networked platform through observation and registration the research will not involve communication with respondents. The information that is gathered will only be registered if the user has a public account. In this case, the user has agreed towards the online network that others can view his or her personal information (Last FM, 2013).

3.3 Measures

The sample population of Last.fm shall be observed to measure the needed secondary data. Last.fm is an online-networked music streaming platform and a controlled environment to test the hypotheses, because of specific datasets that can be extracted through API coding. The data will be retrieved through API (Application Program Interface) links into an excel format with the coding language JSON. APIs extract public data from Last.fm and allow the data to be used for applications, websites or research if the terms of use are met. This allows for no involvement of respondents or skewed data because of subjective opinions. It also allows for real online data to be acquired in very high quantity.

3.4 Reliability and Validity

A large amount of respondents with truthful answers about their network is needed to study the effect of recommendation with certain characteristics in an online-networked platform. Respondents often have no grasp on how their followers are spread among a social structure. Therefore, it is important to not let the respondents interfere with the observed data.

Quantitative research without the interference of respondents and directly taken from the online-networked platform can then be used to create a reliable and valid study. The validity and reliability of quantitative research is defined by the sample size of the targeted population and the extent in which the study results will be objectively correct regarding the population.

3.4.1 Reliability

The quantitative research must be reliable, where coincidental errors are minimized. The study is considered reliable, because the sample of the population that is examined will be 3.000 respondents, with a confidence level of 95% and an error margin of 5% (Raosoft, Inc., 2004). The respondents will be analysed in three stages, adding 500 users in each stage to monitor for large fluctuation of results. The minimum amount that is needed to have a reliable sample is 385 respondents. The use of secondary data allows for huge datasets with a very high confidence level.

3.4.2 Validity

The quantitative research must be valid to give truthful meaning to the findings of the research. The study is considered valid, because the data is not compromised by respondents or researchers influence. This minimizes human interference and solely registers the factual data from the online-networked platform on characteristics and recommendation rates of users. Therefore the data is objective and a sample representation of data for the online-networked platform community.

3.5 Procedure and Analytic Plan

The study will follow the three specified questions and answer them by registering the findings and testing the hypotheses that will be rejected or fail to be rejected, depending on the results.

The first specified research question is to assess the characteristics of users on the Last.fm platform. To provide an answer the user nationality, song play count and friend count is observed and registered through API calling.

The second specified research question is to assess the recommendation rate of users on the Last.fm platform. To provide an answer the recently listened new music of a user is compared with the recently listened new music of the users friends. The amount of positive comparisons between the user and the users friends is called the recommendation rate.

The third specified research question is to analyse the statistically significant effect of the association between the characteristics and the recommendation rate of users on the Last.fm platform. To provide an answer the hypotheses are tested in SPSS.

The data will first be observed with exploratory regression analyses. This will give an indication of the relations between the variables. H1 will then be tested in SPSS using an ordinal regression analysis to propose that users within the age group of 14 to 20 years old have a positive effect on the recommendation rate variable regarding new music. H2 and H3 will be tested in SPSS using a bivariate correlation analysis and a linear regression model to propose that the user song play count and friend count have a positive effect on the recommendation rate regarding new music. H4 and H5 will be tested in SPSS using a linear regression analysis with nominal dummy variables to propose that users from West-Europe and the U.S. and the genre pop and rock have a positive effect on the association between the characteristics and recommendation rate of a user regarding new music. An overview of the tests and variables is found in Appendix B.

4. RESULTS

Data was collected through API calls for 3.144 users of the online-networked platform Last.fm and analysed using SPSS. After analysing 2.061 observations, 500 users were added to the sample to monitor potential fluctuation of the results. Then the final group of 583 users were added to further examine potential fluctuation of the results. The observations were analysed in SPSS using regression models. The results of the analyses are discussed in this chapter following the order of the formulated hypotheses.

4.1 Hypothesis I

The age of users was not retrievable through API coding, even though API examples of Last.fm showed data regarding age. It could be assumed that this data was available to enter in the past, but in the timeline of this research no measure to collect age demographics for the collected users was found. However, age demographics of 2010 and 2012, as shown in appendix C, give some insight in the distribution of last.fm age groups and the effect of genre on those age groups.

Figure 8 shows that 68% of the Last.fm community is between 25 and 54 years old. 20% is between the 25 and 34 years old, 25% is between the 35 and 44 years old and 23% is between the 45-54 years old. Figure 7 shows that younger age groups have more expressed listening preferences and spent more time on the platform compared to older age groups. Figure 7 also shows that pop and rock are dominant genres with the preference of younger age groups.

These findings are not proven statistically significant however. A relation between age groups and the recommendation rate of users in an online-networked platform is not found. Therefore it can be stated that age groups between 14 and 20 years old do not necessarily have a higher recommendation rate. The expectation of hypothesis I is rejected.

4.2 Hypothesis II

To test the hypothesis that a higher song play count has a positive effect on the recommendation rate in an online-networked social platform, a linear regression model was conducted in SPSS as shown in appendix D, table 2.1, 2.2 and 2.3. The mean song play count of users is 63.647 songs with a Standard Deviation (*SD*) of 2,37. A P value (*P*) of 0,000 indicates there is a significant relationship between the song play count and the recommendation rate with a beta value (*B)* of 0,238, which indicates a weak relationship according to the relationship strength theory by Cohen (1988). However, this significance only accounts for (0,238^2 * 100 =) 5,66% (*R Square*) of the variance between the two variables. The R square (3,5%) and beta value (*B* = 0,186) slightly decrease when more users are tested, although the relation stays significant (*P* = 0,000 *SD* = 2,37) and positive. Table 1.7 shows the data results hypothesis II.

Hypothesis 2	R Square	P-value	St. Dev.	Beta
User song play count	3,5%	0,000	2,37	0,186

Table 1.7: Hypothesis II results values with 3.144 users

The correlation is therefore not strong, but it does have a positive effect on the recommendation rate. It can be implied that users who listen to more songs positively influence the recommendation rate. Therefore hypothesis II can't be rejected and will be accepted for now.

4.3 Hypothesis III

To test the hypothesis that a higher friend count has a positive effect on the recommendation rate in an online-networked platform, a linear regression model was conducted in SPSS as shown in appendix D, table 3.1, 3.2 and 3.3. The mean amount of friends a user has is 276 with a standard deviation of 2,39. The value that occurs most often however is 1 friend. The linear relation between the friend count and the recommendation rate is significant (P = 0,000 SD = 2,39) with a beta value of 0,211, which indicates a weak relation according to Cohen (1988). Also, it only accounts for (0,211^2 * 100 =) 4,40% (*R Square*) of the variance between the friend count and recommendation.

When a non-linear regression is added by using a squared friend count variable in the linear regression, the findings are significant (P = 0,000 SD = 2,37) with beta values of 0,435 and -0,246 and accounts for 5,5% of the variance. The negative relation of the non-linear regression shows that followers above a certain level negatively impact the recommendation rate. It could be implied that users with a great amount of followers are less likely to act as an effective influencer compared to users with fewer followers. When more users are tested, both relations stay significant (P = 0,000 SD = 1,99 for both). The R Square (linear: 2,4%, non-linear: 2,6%) and beta values (B = 0,249 and B = -0,105) decrease slightly, but the non-linear relation becomes slightly less negative. Table 1.8 shows the data results of hypothesis III.

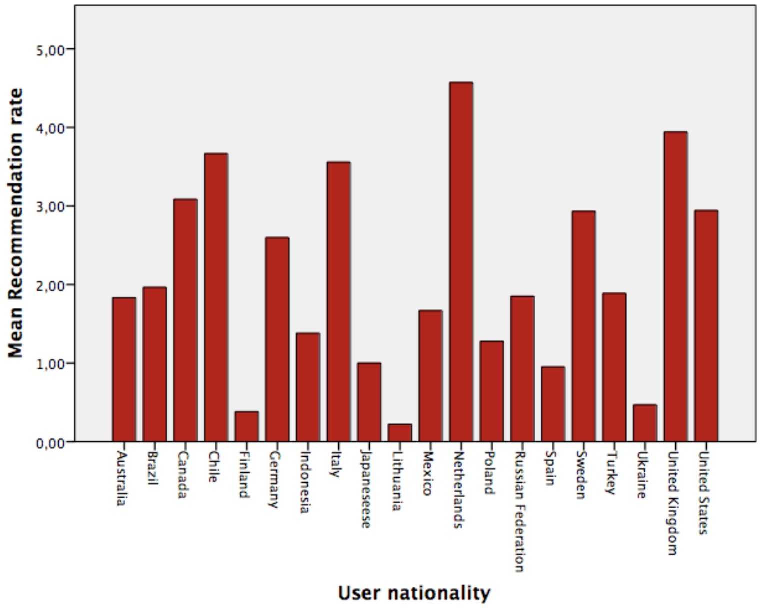
Hypothesis 3 linear	R Square	P-value	St. Dev.	Beta
Friend count	2,4%	0,000	2,37	0,249
Hypothesis 3 non-linear				
Friend count	2,6%	0,000	1,99	-0,105

Table 1.8: Hypothesis III results values with 3.144 users

It can be implied that big data samples show a less negative relation between the non-linear friend count regression and the recommendation rate, although the percentage of variance decreases too. The relation remains negative, so it can be stated that users with a higher friend count do not necessarily have a higher recommendation rate. The expectation of hypothesis III can be rejected.

4.4 Hypothesis IV

The mean recommendation rates of the nationalities were compared with each other to see what nationalities would generate a higher recommendation rate without other variables. Graph 1.6 shows the histogram of mean recommendation rates per nationality.



Graph 1.6: Mean recommendation rate of nationalities histogram

This does not mean that the high recommendation rates on European countries and the U.S. prove a positive relation with all variables considered. To test the hypothesis that users with a nationality from the U.S. or Europe have a positive effect on the relation between the characteristics and the recommendation rate of a user, a multiple regression analysis with categorical dummy variables was conducted in SPSS as shown in appendix D, table 4.1 to 4.6. The findings are that user nationality accounts for 2,6% (*R square* = 0,026) of the variance between the song count and the recommendation rate. In total the song count and nationality account for 8,3% (*R square* = 0,083) of the variance. The nationalities that were significant (*P* = 0,000 *SD* = 2,35) had a slightly positive effect on the relation between the song count and the recommendation rate, consisting of the United States (*B* = 0,066), United Kingdom (*B* = 0,056) and Chile (*B* = 0,089). A larger dataset causes the total R Square (5,4%) to slightly decrease, but the significant (*P* = 0,000 *SD* = 1,97) beta values for the United States (*B* = 0,084) and the United Kingdom (*B* = 0,058) increase. The values for France (*B* = 0,042) and Turkey (*B* = 0,039) become significant and positive and Chile (*B* = 0,043) decreases in value. Table 1.9 shows the data results of hypothesis IV regarding play count.

Hypothesis 4	R Square	P-value	St. Dev.	Beta
User song play count	5,4%	0,000	1,97	0,154
United States	5,4%	0,000	1,97	0,084
United Kingdom	5,4%	0,002	1,97	0,088
France	5,4%	0,018	1,97	0,060
Turkey	5,4%	0,027	1,97	0,054
Chile	5,4%	0,015	1,97	0,043

Table 1.9: Hypothesis IV results values I with 3.144 users

The nationality also accounts for 2,6% (R square = 0,026) of the variance between the friend count and the recommendation rate. In total the friend count and nationality account for 8% (R square = 0,080) of the variance. The significant (*P* = 0,000 *SD* = 2,35) nationalities United Kingdom (B = 0,089), Turkey (B = 0,055) and France (B = 0,059) had a slightly positive effect on the relation between the friend count and recommendation rate. Canada (B = -0,047) and Ukraine (B = -0,045) have a slightly negative interaction with the tested relationship. A larger dataset decreases the R Square (4,9%), but increases the significant (P = 0,000 SD = 1,93) positive effect of France (B = 0,060). The Beta values for the United Kingdom (B = 0,088) and Turkey (B = 0,054) minimally decrease in value, but stay positive. Ukraine and Canada no longer have a statistically significant effect with the larger data set. Table 1.10 shows the data results of hypothesis IV regarding friend count.

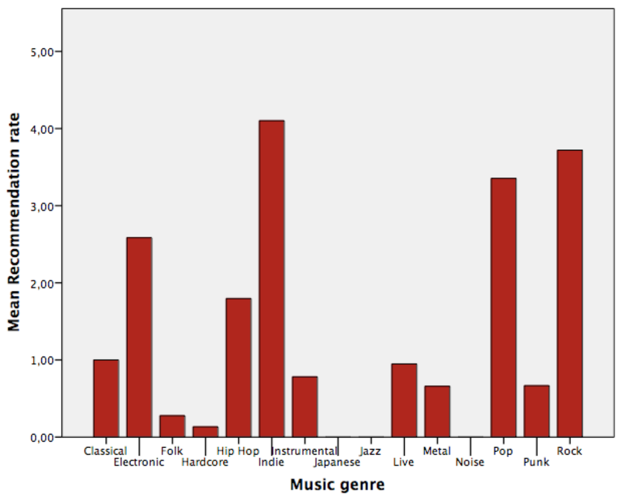
Hypothesis 4	R Square	P-value	St. Dev.	Beta
Friend count linear	4,9%	0,000	1,97	0,000
Friend count non-linear	4,9%	0,015	1,97	-0,083
United Kingdom	4,9%	0,000	1,97	0,088
France	4,9%	0,002	1,97	0,060
Turkey	4,9%	0,002	1,97	0,054

Table 1.10: Hypothesis IV results values II with 3.144 users

The interaction effect is not strong, but it could be implied that representing a nationality in Europe or the U.S. positively influences the desired effect of a higher recommendation rate either through friend count or play count. It can be implied that users with a nationality from the U.S. or Europe positively influence the recommendation rate in the relation between either the user song play count, the friend count and recommendation rate. Therefore hypothesis IV can't be rejected and will be accepted for now.

4.5 Hypothesis V

The mean recommendation rates of music genres were compared with each other to see what genres would generate a higher recommendation rate without the interference of other variables. Graph 1.7 shows the histogram of mean recommendation rates per music genre. This does not mean that the high recommendation rates on the music genre pop and rock prove a positive relation with all variables considered.



Graph 1.7: Mean recommendation rate of music genres histogram

To test the hypothesis that the music genre pop and rock have a higher recommendation rate in the relation between the characteristics and recommendation rate of a user regarding new music, a multiple regression analysis with categorical dummy variables was conducted in SPSS as shown in appendix D, table 5.1 to 5.6. Music genre accounts for 2,9% (*R Square* = 0,029) of the variance between the song play count and the recommendation rate. The total variance of the song play count and music genre is 8,5% (*R Square* = 0,085). The genres that were found significant (P = 0,000 SD = 2,35) have a positive interaction with the tested relationship. The genres pop (B = 0,052), rock (B = 0,077) and electronic (B = 0,075) are positively interacting with the relationship, but are outperformed by the genre indie (B = 0,127). A larger dataset decreases the total variance to 5,4% (*R Square* = 0,054) and of the significant genres (P = 0,000 SD = 1,97) it decreases the genre indie (B = 0,104) and rock (B = 0,062) slightly. The effect of electronic music slightly increased with a sample of 2.561 users, but then lowered back to a beta value of 0,075 with a sample of 3.144 users. Table 1.11 shows the data results of hypothesis V regarding play count.

Hypothesis 5	R Square	P-value	Std. Dev.	Beta
User song play count	5,4%	0,132	1,97	0,000
Indie	5,4%	0,000	1,97	0,104
Rock	5,4%	0,001	1,97	0,062
Electronic	5,4%	0,000	1,97	0,075

Table 1.11: Hypothesis V results values I with 3.144 users

The music genre marginally affected the relation between the friend count and the recommendation rate with 0,9% (*R Square* = 0,009) of the variance explained by genre. The total variance explained by the genre and friend count together was 6,4% (*R Square* = 0,064). The only statistically significant (P = 0,035 SD = 2,39) music genre was a positive interaction of electronic music (B = 0,047) on the tested relation. When more users are tested, the total R Square (4,4%, 3,4%) decreases. Electronic music (B = 0,058) increases in positive Beta value, and pop becomes statistically significant and has a slightly negative effect on the tested relation. Table 1.12 shows the data results of hypothesis V regarding friend count.

Hypothesis 5	R Square	P-value	Std. Dev.	Beta
Friend count linear	3,4%	0,000	1,99	0,231
Friend count non-linear	3,4%	0,005	1,99	-0,098
Electronic	3,4%	0,002	1,99	0,047
Pop	3,4%	0,023	1,99	-0,042

Table 1.12: Hypothesis V results values II with 3.144 users

Pop has a slightly negative effect on the recommendation rate through the characteristics contrary to expectations. It can be implied that indie and electronic music have a more positive effect on the relation between the characteristics and the recommendation rate compared to other genres. Therefore it can be stated that the music genre pop and rock don't necessarily influence the recommendation rate positively in the relation between the characteristics and recommendation rate. Hypothesis V can be rejected.

5. DISCUSSION POINTS

This chapter seeks to discuss the meaning of the results and provide a context to how the results fit in the existing literature. It starts with an overview of the study and proceeds to discuss the relevant findings.

5.1 Overview of the study

This study researched the influence of user characteristics on the recommendation rate of new music. The main objective was:

To analyse the relation between the characteristics and recommendation rate of a user in an online-networked music platform.

This was studied by assessing the user characteristics and recommendation rate to analyse the relation between the variables. Regression analysis was used in SPSS to search for positive relations between the characteristics of users, consisting of the play count and friend count, and the recommendation rate for new music. The nationality of users and music genre of recommended songs were used as moderators to test the correlation between the characteristics and the recommendation rate. Although the R Square values were low, the P-values indicated that the positive relationship between the characteristics and the recommendation rate was significant and positively influenced by nationalities from the U.S. and Europe. Table 1.13 shows the hypotheses and the association as a result of the present research.

Hypothesis	Association
Hypothesis I	Discarded
Hypothesis II	Accepted
Hypothesis III	Rejected
Hypothesis IV	Accepted
Hypothesis V	Rejected

Table 1.13: Association of the hypotheses

5.2 Discussion of the Findings

The literature showed that previous studies on the influence of age on music found a relation between the importance of music and adolescents on a social and cognitive level (A.C. North, et al, 2000). Data could not be collected through API calls and only interpreted through secondary data that was collected in 2010 and 2012. The data suggests a higher involvement and more diverse genre preference with younger age groups, but can't be tested for statistical significance. This suggestion agrees with the literature, but can't be validated without further research.

Experience and time investment have been shown to be indicators of influencer's credibility in previous studies (Wiedmann, K. P, 2007; Freberg, K, et al, 2011). The literature also showed that credibility positively influences recommendation (M. López and M. Sicilia, 2014). The present results show that there is a statistically significant, positive relation between the amount of songs a user listens to and the recommendation rate of a user in an online-networked platform. These findings agree with the literature, although the relation is relatively weak. This could be explained by the ease of listening to music and spending time on the online-networked platform while performing other activities.

These studies also showed that increased levels of followers or friends positively correlate with the credibility of influencers (Freberg, K, et al, 2011; López, M., & Sicilia, M., 2014). The present results also show that the relation is strongly positive and then weakens to a slightly negative relation. This could indicate that users with a lot of followers positively influence the recommendation rate, but when it reaches a certain quantity, the positive relation saturates and doesn't further increase with more followers. Another explanation could be that users could lose the music interest of followers and potentially become too 'generic' in an attempt to satisfy all follower preferences. The findings agree partly with the literature, but imply that the relation between the friend count and recommendation rate in an online-networked platform can be refined to positive until saturation occurs at high follower levels.

A research by R.J. Crisp, et al (2011) on influencers and different cultures showed that social or cultural conflicting frames tend to cause stress or marginalization of a positive effect. If the conflicting frame is integrated however, the experience can lead to a positive effect. The present results show that the U.S. and European nationalities have a positive effect on the relation between the characteristics and the recommendation rate of users. These findings agree with the literature, although the relation is fairly weak. This can be explained by the globalization of western culture (Pieterse, J. N., 2015) and with it the integration of modern music where all nationalities slowly integrate into the frame of western music recommendation.

Previous studies have shown that familiarity and liking music have a positive relationship (North, A.C., and Hargreaves, D.J., 1995). Familiarity is strongly present in middle-of-the-road genres like pop and rock (Tagg, P., 1982). The present results show that the music genre pop and rock don't necessarily influence the recommendation rate positively in the relation between the characteristics and recommendation rate. The pop genre even had a slightly negative effect. These findings conflict with the literature and could be influenced by preference changes of the online-networked community compared to 1995. Another explanation could be that followers of new music influencers are more interested in unknown music compared to familiar pop singles released by renowned artists. This suggestion however can't be validated without further research.

The music genre indie and electronic have a positive influence on the tested relationship, contrary to the expectations of the hypothesis. These findings agree with the suggestion of changed preferences compared to the A.C. North study from 1995. Another explanation could be the popularity of electronic and indie music compared to pop and rock music. The genre popularity could be tested in a study on genre popularity among online-networked social platforms to validate this assumption.

6. CONCLUSION, LIMITATIONS AND RECCOMMENDATIONS FOR FURTHER STUDY

This chapter summarizes the purpose of this study and addresses the implications and limitations of the present research. Finally, in the conclusion the interpreted results are summarized and the final conclusion is formulated.

6.1 Summary

This study is an attempt to uncover characteristics of users who influence their network effectively with new music recommendation in an online-networked social platform. The importance of Word of Mouth and growth of music streaming networks enhanced the peer-to-peer recommendation and created a growing need for the understanding of identifiers of influencers. These studies are not only relevant for academics of social behaviour, but also for the music industry. When new talent as well as professional bands or agencies understand the identification of influencers, they could take advantage of the information on the music diffusion by using digital marketing outlets.

6.2 Hypothetical scenario

To show the gain in income by targeting effective influencers in an online-networked social music-streaming platform, 100 random users and 100 influencers were selected from the real life dataset to compare the potential album sales of a newly released album. The managerial literature showed the importance of artist's album page traffic and the potential sales conversions through Itunes, Amazon and e-Bay as depicted in figure 3.

Suppose an indie music artist releases a new album and can send 100 previews to users in the online-networked social platform. When the random sample of 100 users is measured on recommendations the total friend count is multiplied by the percentage recommendation rate. This shows the diffusion of the music through 100 random users. According to the dataset a random set of users diffuses the music among a total of 556 followers who see and listen to the new music through peer-to-peer recommendation. Given an average conversion of 4% for e-commerce (SmartInsights, 2017), the potential album sales would be (556 users * 4%) 22 albums with an average price of $13.

When the targeted users are specified towards the characteristics of influencers as researched in the present study, the diffusion would rise to 6884 users, given the users are positively influenced by the song play count, nationality and the music genre. This amounts to an income gain of ((6884 * 4%) - 22) 253 sold albums with an average price of $13. The marketing efforts through the music-streaming platform Last.fm are free from charge. This means that an estimated net income is multiplied 11.5 times by targeting identified influencers instead of random users, given the observed recommendation rates are established and the average conversion rate for e-commerce is met.

6.3 Limitations and Recommendations for Further Study

The present study has a few limitations that should be acknowledged. The research attempted to find causal relations, but the results and practice show that only associations could be found. Causal relations may not have been found due to the homophily of users and marketing issues. Even though no recommendations have been found for some users, they may have influenced followers outside of the online-networked platform, what caused the association. Marketing and radio outlets may also have caused an association for influencers as well as influenced followers. Causal analysis for online-networked platforms can be researched with matched sample estimation by matching two users in a controlled environment to see if they influence each other (Aral, S, et al, 2009). Further, the independent variable age could not get data related to the present user dataset. This limited the analyses that could be done and may have caused the age related findings to be out-dated. Lastly, the analyses showed a small R Square, meaning that the significance of the tests accounted for a small percentage of the variance between the tested variables. An explanation for this would be that human behaviour is always harder to predict and expects the R Square to be lower. Another explanation would be that from a large dataset only a small percentage recommends new music to followers as shown by the low mode and median values.

Researchers may consider using Spotify data instead of Last.fm data to control for this research and check for similarities and differences in the associations that were found. This could give more understanding on the influencer characteristics across multiple platforms. Future research can also use the present study's methodology and research for a larger dataset. This could give researchers a more accurate insight on online-networked influencers of new music. The API call method allows for high quantities of users given enough time to collect. Finally, further studies could research the influence of 'popular' music on the positive correlation between music genre and recommendation rate. This could give a better understanding into why certain genres are positively correlated with the recommendation rate. These studies may find a relation between current popular music and positively correlating music genres with the recommendation rate. Academics, as well as the music industry, could take advantage of those findings to be able to predict effective influencers with popular genres.

6.4 Conclusion

This study sought to answer the main question that was formulated in chapter I, the research objective:

What user characteristics influence the recommendation rate of a user in an online-networked music platform regarding new music?

The research showed that when a user has more experience and time spent on the online platform, the recommendation rate is positively related. The amount of followers a user has is also positively related to the recommendation rate of a user until high levels of followers saturate the positive relation. Furthermore, nationalities from the U.S. and Europe have a positive influence on the relation between the characteristics and the recommendation rate, similar to the indie and electronic music genre.

In other words, according to the present research the most influential users regarding new music in an online-networked social music-streaming platform have the following characteristics. They have more experience and time spent on the online platform, together with a higher friend count, compared to other users on the platform. For the platform of Last.fm that would mean an amount above the mean value, namely a song count above the 63.647 songs and slightly above 276 followers. The user has a nationality from the U.S. or a European country like the United Kingdom, France or Turkey. Lastly, the influence on the users network will slightly increase with music of the genre pop and rock. The user influence on their network will be the greatest with music of the genre indie and electronic.

The present study showed that these characteristics positively correlate and influence the diffusion of new music in an online-networked social music-streaming platform. Marketing efforts in the music industry could use these characteristics in targeting influencers to effectively diffuse new music among consumers.

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APPENDIXES

Appendix A

What user characteristics influence the recommendation rate of a user in an online-networked music platform regarding new music?

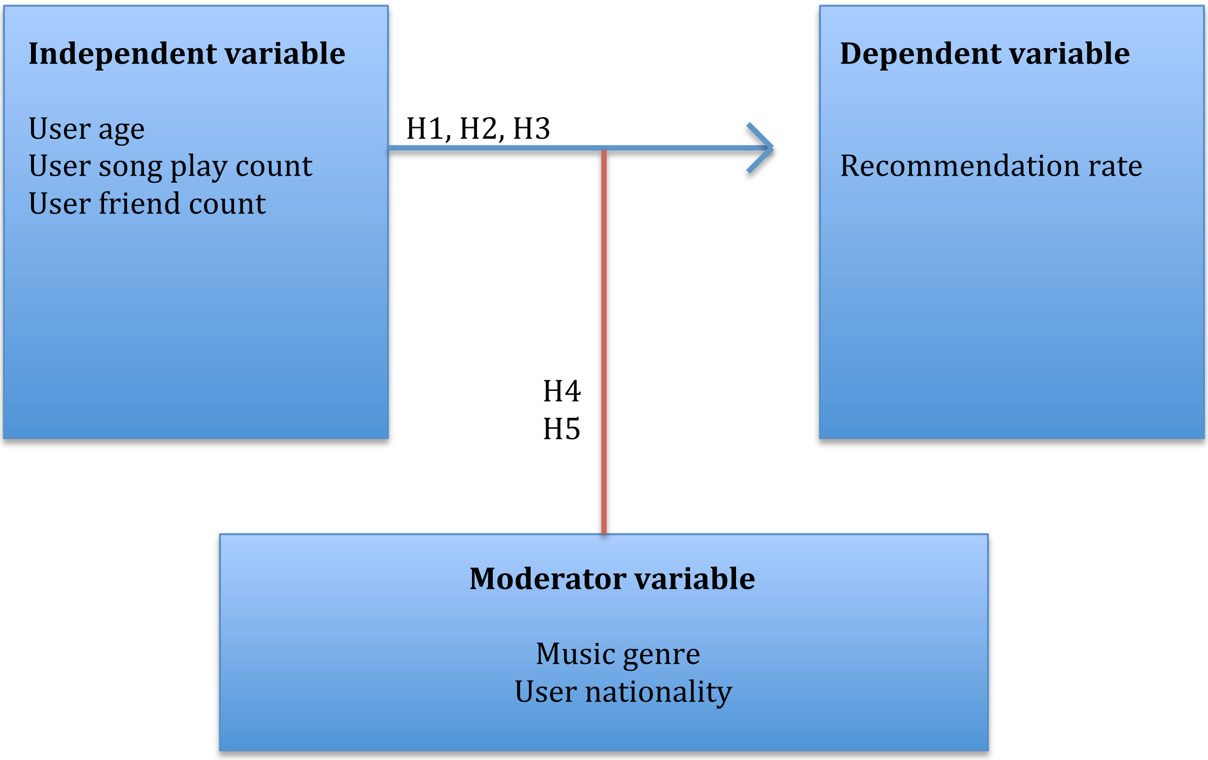


Figure II Schematic visualization of this study's conceptual framework

Appendix B

Research Recommendation in online networks

Variables	Metric level	modifciation
Independent variables		
Age	Ordinal	Mode, median, freq. table
Song count	Scale	Mode, median and mean
Friend count	Scale	Mode, median and mean
Dependent variable		
Recommendation rate	Scale	Mode, median and mean
Moderator variable		
Nationality	Nominal	Mode, Freq. table
Music genre	Nominal	Mode, Freq. table

Hypothesis 1	Age	\	Ordinal	Relation	Ordinal regression analysis
	Recommendation rate	/	Scale		
Hypothesis 2	Song count	\	Scale	Relation	Linear regression analysis
	Recommendation rate	/	Scale		
Hypothesis 3	Friend count	\	Scale	Relation	Linear regression analysis
	Recommendation rate	/	Scale		
Hypothesis 4	Age	\	Ordinal		
	Recommendation rate		Scale	Interaction	Ordinal regression analysis
	Nationality	/	Nominal		
	Song play count	\	Scale		
	Recommendation rate		Scale	Interaction	Linear regression analysis
	Nationality	/	Nominal		
	Friend count	\	Scale		
	Recommendation rate		Scale	Interaction	Linear regression analysis
	Nationality	/	Nominal		
Hypothesis 5	Age	\	Ordinal		
	Recommendation rate		Scale	Interaction	Ordinal regression analysis
	Music Genre	/	Nominal		
	Song play count	\	Scale		
	Recommendation rate		Scale	Interaction	Linear regression analysis
	Music Genre	/	Nominal		
	Friend count	\	Scale		
	Recommendation rate		Scale	Interaction	Linear regression analysis
	Music Genre	/	Nominal		

Appendix C

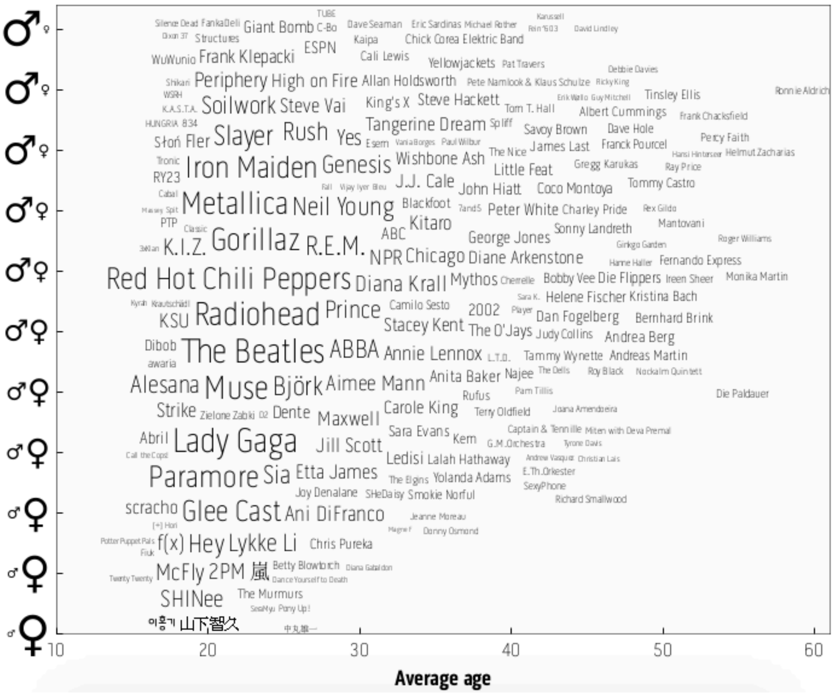


Figure V. Age, gender and preference demographic of a Last.fm sample dataset in 2010. Reprinted from Music preferences by gender, in Flowing data, n.d., Retrieved July 26, 2017, from https://flowingdata.com/2010/09/28/music-listening-preferences-by-gender/

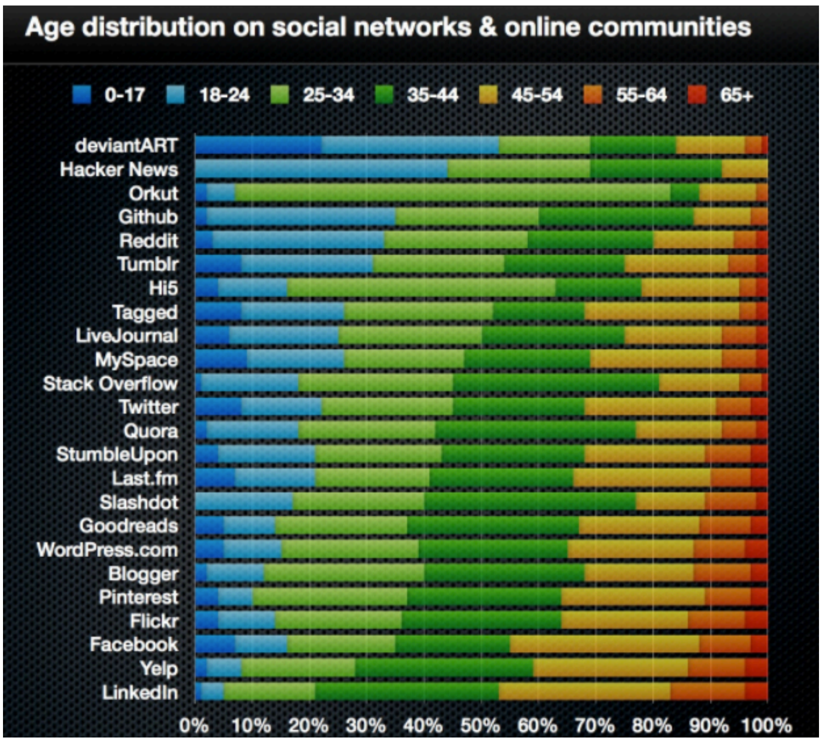


Figure VI. Age demographic of a Last.fm sample dataset in 2012. Reprinted from DoubleClick Ad Planner (Google), in U.S. Demographics, n.d., Retrieved July 26, 2017, from https://www.tnooz.com/article/social-media-demographics-in-2012-research/

Appendix D

FREQUENCIES

User nationality

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	United States	336	19,4	19,4	19,4
	United Kingdom	174	10,0	10,0	29,4
	Ukraine	25	1,4	1,4	30,9
	Turkey	25	1,4	1,4	32,3
	Sweden	20	1,2	1,2	33,5
	Spain	15	,9	,9	34,3
	Russian Federation	166	9,6	9,6	43,9
	Poland	86	5,0	5,0	48,9
	Netherlands	44	2,5	2,5	51,4
	Mexico	18	1,0	1,0	52,5
	Lithuania	11	,6	,6	53,1
	Italy	25	1,4	1,4	54,5
	Indonesia	94	5,4	5,4	60,0
	Germany	84	4,8	4,8	64,8
	France	5	,3	,3	65,1
	Finland	33	1,9	1,9	67,0
	Chile	21	1,2	1,2	68,2
	Canada	47	2,7	2,7	70,9
	Brazil	480	27,7	27,7	98,6
	Australia	24	1,4	1,4	100,0
	Total	1733	100,0	100,0	

Frequency table 1

Music genre

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Rock	112	12,5	12,5	12,5
	Punk	33	3,7	3,7	16,2
	Pop	162	18,1	18,1	34,4
	Noise	20	2,2	2,2	36,6
	Metal	100	11,2	11,2	47,8
	Live	44	4,9	4,9	52,7
	Jazz	17	1,9	1,9	54,6
	Japanese	13	1,5	1,5	56,1
	Instrumental	53	5,9	5,9	62,0
	Indie	126	14,1	14,1	76,1
	Hip Hop	49	5,5	5,5	81,6
	Hardcore	20	2,2	2,2	83,9
	Folk	21	2,4	2,4	86,2
	Electronic	111	12,4	12,4	98,7
	Classical	12	1,3	1,3	100,0
	Total	893	100,0	100,0	

Frequency table 2

Exploratory Regression analysis: Song play count

Descriptive Statistics

	Mean	Std. Deviation	N
Recommendation rate	,9081	2,50949	2061
User song play count	62165,75	128285,063	2061

Correlations

		Recommendation rate	User song play count
Pearson Correlation	Recommendation rate	1,000	,212
	User song play count	,212	1,000
Sig. (1-tailed)	Recommendation rate	.	,000
	User song play count	,000	.
N	Recommendation rate	2061	2061
	User song play count	2061	2061

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,212[a]	,045	,045	2,45290

a. Predictors: (Constant), User song play count

b. Dependent Variable: Recommendation rate

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	584,503	1	584,503	97,146	,000[b]
	Residual	12388,431	2059	6,017		
	Total	12972,935	2060			

a. Dependent Variable: Recommendation rate

b. Predictors: (Constant), User song play count

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	,650	,060		10,826	,000	,532	,768
	User song play count	4,152E-006	,000	,212	9,856	,000	,000	,000

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	,6500	14,9559	,9081	,53267	2061
Residual	-10,28594	23,67177	,00000	2,45231	2061
Std. Predicted Value	-,485	26,372	,000	1,000	2061
Std. Residual	-4,193	9,651	,000	1,000	2061

a. Dependent Variable: Recommendation rate

Exploratory regression analysis 1

Exploratory Regression analysis: Friend count

Descriptive Statistics

	Mean	Std. Deviation	N
Recommendation rate	,9081	2,50949	2061
User friend count	261,77	1171,735	2061

Correlations

		Recommendation rate	User friend count
Pearson Correlation	Recommendation rate	1,000	,168
	User friend count	,168	1,000
Sig. (1-tailed)	Recommendation rate	.	,000
	User friend count	,000	.
N	Recommendation rate	2061	2061
	User friend count	2061	2061

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,168[a]	,028	,028	2,47460

a. Predictors: (Constant), User friend count

b. Dependent Variable: Recommendation rate

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	364,351	1	364,351	59,499	,000[b]
	Residual	12608,584	2059	6,124		
	Total	12972,935	2060			

a. Dependent Variable: Recommendation rate

b. Predictors: (Constant), User friend count

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	,814	,056		14,577	,000	,705	,924
	User friend count	,000	,000	,168	7,714	,000	,000	,000

a. Dependent Variable: Recommendation rate

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	,8142	10,4005	,9081	,42056	2061
Residual	-10,40055	23,82245	,00000	2,47400	2061
Std. Predicted Value	-,223	22,571	,000	1,000	2061
Std. Residual	-4,203	9,627	,000	1,000	2061

a. Dependent Variable: Recommendation rate

Exploratory regression analysis 2

Exploratory Regression analysis: Play count and friend count

Descriptive Statistics

	Mean	Std. Deviation	N
Recommendation rate	,9081	2,50949	2061
User song play count	62165,75	128285,063	2061
User friend count	261,77	1171,735	2061

Correlations

		Recommendation rate	User song play count	User friend count
Pearson Correlation	Recommendation rate	1,000	,212	,168
	User song play count	,212	1,000	,080
	User friend count	,168	,080	1,000
Sig. (1-tailed)	Recommendation rate	.	,000	,000
	User song play count	,000	.	,000
	User friend count	,000	,000	.
N	Recommendation rate	2061	2061	2061
	User song play count	2061	2061	2061
	User friend count	2061	2061	2061

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,261[a]	,068	,067	2,42398

a. Predictors: (Constant), User friend count, User song play count

b. Dependent Variable: Recommendation rate

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	880,742	2	440,371	74,948	,000[b]
	Residual	12092,192	2058	5,876		
	Total	12972,935	2060			

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	95,0% Confidence Interval for B Lower Bound	95,0% Confidence Interval for B Upper Bound
1	(Constant)	,580	,060		9,637	,000	,462	,698
	User song play count	3,915E-006	,000	,200	9,375	,000	,000	,000
	User friend count	,000	,000	,152	7,101	,000	,000	,000

a. Dependent Variable: Recommendation rate

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	,5797	14,0721	,9081	,65387	2061
Residual	-9,95381	23,73171	,00000	2,42281	2061
Std. Predicted Value	-,502	20,132	,000	1,000	2061
Std. Residual	-4,106	9,790	,000	1,000	2061

a. Dependent Variable: Recommendation rate

Exploratory regression analysis 3

Exploratory Regression analysis: Music genre

Descriptive Statistics

	Mean	Std. Deviation	N
Recommendation rate	,9081	2,50949	2061
musicgenreindie	,04	,202	2061
Musicgenreelectronic	,04	,196	2061
Musicgenrepop	,04	,192	2061
Musicgenrerock	,04	,187	2061
Musicgenremetal	,03	,171	2061
Musicgenreinstrumental	,02	,140	2061
Musicgenrelive	,02	,131	2061
Musicgenrehiphop	,02	,124	2061
Musicgenrepunk	,01	,100	2061
Musicgenrefolk	,01	,088	2061
Musicgenrejazz	,01	,079	2061
Musicgenreclassical	,01	,073	2061
Musicgenrejapanese	,01	,073	2061
Musicgenrenoise	,01	,073	2061
Musicgenrehardcore	,00	,070	2061

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,444[a]	,198	,192	2,25628

a. Predictors: (Constant), Musicgenrehardcore, Musicgenrenoise, Musicgenrejapanese, Musicgenreclassical, Musicgenrejazz, Musicgenrefolk, Musicgenrepunk, Musicgenrehiphop, Musicgenrelive, Musicgenreinstrumental, Musicgenremetal, Musicgenrerock, Musicgenrepop, Musicgenreelectronic, musicgenreindie

b. Dependent Variable: Recommendation rate

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2562,214	15	170,814	33,553	,000[b]
	Residual	10410,720	2045	5,091		
	Total	12972,935	2060			

a. Dependent Variable: Recommendation rate

b. Predictors: (Constant), Musicgenrehardcore, Musicgenrenoise, Musicgenrejapanese, Musicgenreclassical, Musicgenrejazz, Musicgenrefolk, Musicgenrepunk, Musicgenrehiphop, Musicgenrelive, Musicgenreinstrumental, Musicgenremetal, Musicgenrerock, Musicgenrepop, Musicgenreelectronic, musicgenreindie

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	,402	,059		6,833	,000	,286	,517
	musicgenreindie	3,666	,248	,295	14,807	,000	3,181	4,152
	Musicgenreelectronic	1,899	,256	,148	7,418	,000	1,397	2,401
	Musicgenrepop	3,173	,261	,243	12,176	,000	2,662	3,684
	Musicgenrerock	3,202	,267	,239	11,990	,000	2,679	3,726
	Musicgenremetal	,238	,293	,016	,813	,416	-,336	,811
	Musicgenreinstrumental	,362	,357	,020	1,015	,310	-,338	1,063
	Musicgenrelive	,506	,381	,026	1,329	,184	-,241	1,252
	Musicgenrehiphop	,817	,403	,040	2,027	,043	,026	1,608
	Musicgenrepunk	,424	,496	,017	,854	,393	-,549	1,396
	Musicgenrefolk	,015	,567	,001	,027	,979	-1,097	1,127
	Musicgenrejazz	,111	,629	,004	,177	,859	-1,121	1,344
	Musicgenreclassical	,144	,683	,004	,211	,833	-1,195	1,483
	Musicgenrejapanese	-,402	,683	-,012	-,588	,556	-1,741	,937
	Musicgenrenoise	-,402	,683	-,012	-,588	,556	-1,741	,937
	Musicgenrehardcore	-,269	,716	-,007	-,375	,707	-1,673	1,135

a. Dependent Variable: Recommendation rate

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	,0000	4,0680	,9081	1,11525	2061
Residual	-4,06795	20,60205	,00000	2,24805	2061
Std. Predicted Value	-,814	2,833	,000	1,000	2061
Std. Residual	-1,803	9,131	,000	,996	2061

a. Dependent Variable: Recommendation rate

Exploratory regression analysis 4

Exploratory Regression analysis: User nationality

Descriptive Statistics

	Mean	Std. Deviation	N
Recommendation rate	,9081	2,50949	2061
Nationality United States	,12	,329	2061
Nationality Brazil	,12	,323	2061
Nationality United Kingdom	,08	,264	2061
Nationality Russian Federation	,05	,214	2061
Nationality Indonesia	,04	,207	2061
Nationality Poland	,04	,186	2061
Nationality Germany	,03	,179	2061
Nationality Canada	,02	,126	2061
Nationality Finland	,01	,116	2061
Nationality Netherlands	,01	,107	2061
Nationality Turkey	,01	,105	2061
Nationality Ukraine	,01	,098	2061
Nationality Sweden	,01	,096	2061
Nationality Italy	,01	,090	2061
Nationality Japanese	,01	,088	2061
Nationality Australia	,01	,085	2061
Nationality Spain	,01	,085	2061
Nationality France	,01	,079	2061
Nationality Mexico	,01	,076	2061
Nationality Lithuania	,01	,073	2061
Nationality Chile	,00	,070	2061

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,191[a]	,037	,027	2,47584

a. Predictors: (Constant), Nationality Chile, Nationality Lithuania, Nationality Mexico, Nationality France, Nationality Spain, Nationality Australia, Nationality Japanese, Nationality Italy, Nationality Sweden, Nationality Ukraine, Nationality Turkey, Nationality Netherlands, Nationality Finland, Nationality Canada, Nationality Germany, Nationality Poland, Nationality Indonesia, Nationality Russian Federation, Nationality United Kingdom, Nationality Brazil, Nationality United States

b. Dependent Variable: Recommendation rate

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	474,258	21	22,584	3,684	,000[b]
	Residual	12498,677	2039	6,130		
	Total	12972,935	2060			

a. Dependent Variable: Recommendation rate

b. Predictors: (Constant), Nationality Chile, Nationality Lithuania, Nationality Mexico, Nationality France, Nationality Spain, Nationality Australia, Nationality Japanese, Nationality Italy, Nationality Sweden, Nationality Ukraine, Nationality Turkey, Nationality Netherlands, Nationality Finland, Nationality Canada, Nationality Germany, Nationality Poland, Nationality Indonesia, Nationality Russian Federation, Nationality United Kingdom, Nationality Brazil, Nationality United States

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	,526	,087		6,079	,000	,356	,696
	Nationality United States	,816	,178	,107	4,597	,000	,468	1,164
	Nationality Brazil	,508	,181	,065	2,811	,005	,154	,863
	Nationality United Kingdom	1,171	,217	,123	5,399	,000	,746	1,596
	Nationality Russian Federation	,558	,263	,048	2,119	,034	,042	1,075
	Nationality Indonesia	-,033	,272	-,003	-,121	,904	-,567	,501
	Nationality Poland	-,030	,301	-,002	-,101	,920	-,620	,559
	Nationality Germany	1,180	,312	,084	3,776	,000	,567	1,793
	Nationality Canada	1,303	,440	,065	2,963	,003	,441	2,165
	Nationality Finland	,165	,476	,008	,346	,729	-,768	1,098
	Nationality Netherlands	1,169	,513	,050	2,279	,023	,163	2,174
	Nationality Turkey	,228	,523	,010	,435	,664	-,799	1,254
	Nationality Ukraine	-,259	,560	-,010	-,462	,644	-1,358	,840
	Nationality Sweden	,281	,575	,011	,489	,625	-,846	1,408
	Nationality Italy	,572	,607	,021	,943	,346	-,617	1,762
	Nationality Japanese	,349	,625	,012	,559	,577	-,877	1,575
	Nationality Australia	-,037	,645	-,001	-,058	,954	-1,302	1,228
	Nationality Spain	,141	,645	,005	,218	,827	-1,124	1,406
	Nationality France	2,243	,692	,071	3,240	,001	,885	3,600
	Nationality Mexico	,252	,720	,008	,351	,726	-1,159	1,664
	Nationality Lithuania	-,405	,751	-,012	-,539	,590	-1,879	1,069
	Nationality Chile	1,874	,788	,052	2,379	,017	,329	3,419

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	,1209	2,7685	,9081	,47981	2061
Residual	-2,76846	22,97316	,00000	2,46319	2061
Std. Predicted Value	-1,641	3,877	,000	1,000	2061
Std. Residual	-1,118	9,279	,000	,995	2061

a. Dependent Variable: Recommendation rate

Exploratory regression analysis 5

H2: Linear regression user play count

Excluded outliers with the Mahalanobis function

N = 2.061

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	,238[a]	,057	,056	2,37907	,057	122,418	1	2039	,000	1,915

a. Predictors: (Constant), User song play count

b. Dependent Variable: Recommendation rate

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	692,882	1	692,882	122,418	,000[b]
	Residual	11540,671	2039	5,660		
	Total	12233,553	2040			

a. Dependent Variable: Recommendation rate

b. Predictors: (Constant), User song play count

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	,409	,067		6,066	,000
	User song play count	8,742E-006	,000	,238	11,064	,000

a. Dependent Variable: Recommendation rate

Table 2.1: Linear regression I, N = 2061

A scatterplot is made in the exploratory regressions and shows that the homoscedasticity is not tenable (no cigar shape) and that linearity can only be assumed through the residual plot.

The relation between the play count and the recommendation rate is weakly significant (0.238) according to the significance levels of Cohen (1988).

This accounts for (0.238^2 * 100 =) 5,66% (R Square) of the variance between play count and recommendation rate.

N = 2.561

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	,210[a]	,044	,044	1,93432	,044	116,209	1	2518	,000	1,927

a. Predictors: (Constant), User song play count

b. Dependent Variable: Recommendation rate

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	434,805	1	434,805	116,209	,000[b]
	Residual	9421,312	2518	3,742		
	Total	9856,117	2519			

a. Dependent Variable: Recommendation rate

b. Predictors: (Constant), User song play count

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	,228	,048		4,778	,000
	User song play count	5,800E-006	,000	,210	10,780	,000

a. Dependent Variable: Recommendation rate

Table 2.2: Linear regression II, N = 2561

N = 3.144

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	,186[a]	,035	,034	1,99198	,035	111,384	1	3101	,000	1,950

a. Predictors: (Constant), User song play count

b. Dependent Variable: Recommendation rate

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	441,971	1	441,971	111,384	,000[b]
	Residual	12304,766	3101	3,968		
	Total	12746,737	3102			

a. Dependent Variable: Recommendation rate

b. Predictors: (Constant), User song play count

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	,260	,047		5,578	,000
	User song play count	5,825E-006	,000	,186	10,554	,000

a. Dependent Variable: Recommendation rate

Table 2.3: Linear regression III, N = 3144

H3: Linear regression: Friend count

Excluded outliers with the Mahalanobis function

N = 2.061

Bivariate correlation model:

Descriptive Statistics

	Mean	Std. Deviation	N
User friend count	261,77	1171,735	2061
Recommendation rate	,9081	2,50949	2061

Correlations

		User friend count	Recommendation rate
User friend count	Pearson Correlation	1	,168**
	Sig. (2-tailed)		,000
	N	2061	2061
Recommendation rate	Pearson Correlation	,168**	1
	Sig. (2-tailed)	,000	
	N	2061	2061

**. Correlation is significant at the 0.01 level (2-tailed).

A scatterplot is made in the exploratory regressions and shows that the homoscedasticity is not tenable (no cigar shape) and that linearity can only be assumed through the residual plot.

The relation between the friend count and the recommendation rate is weakly significant (0.211) according to the significance levels of Cohen (1988).
This accounts for (0.211^2 * 100 =) 4.40% (R Square) of the variance between friend count and recommendation rate.

Model Summary[c]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,211[a]	,044	,044	2,39087	,044	94,563	1	2035	,000	
2	,234[b]	,055	,054	2,37871	,010	21,872	1	2034	,000	1,864

a. Predictors: (Constant), User friend count
b. Predictors: (Constant), User friend count, friendcount_squared
c. Dependent Variable: Recommendation rate

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	540,551	1	540,551	94,563	,000[b]
	Residual	11632,633	2035	5,716		
	Total	12173,184	2036			
2	Regression	664,306	2	332,153	58,702	,000[c]
	Residual	11508,879	2034	5,658		
	Total	12173,184	2036			

a. Dependent Variable: Recommendation rate
b. Predictors: (Constant), User friend count
c. Predictors: (Constant), User friend count, friendcount_squared

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	,653	,057		11,403	,000
	User friend count	,001	,000	,211	9,724	,000
2	(Constant)	,536	,062		8,603	,000
	User friend count	,003	,000	,435	8,278	,000
	friendcount_squared	,000	,000	-,246	-4,677	,000

a. Dependent Variable: Recommendation rate

Table 3.1: Linear regression I, N = 2061

When friend count is squared (friend count * friend count) the R square changes to 5,5%, with a 1,1% change. The B value of the friend count squared is slightly negative. This means that at a certain level the recommendation rate will go down with higher number of followers. The linear and non-linear regression models together account for 5,5% of the test variance.

N = 2.561

Model Summary[c]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
					Change Statistics					
1	,175[a]	,031	,030	1,96683	,031	79,882	1	2531	,000	
2	,180[b]	,032	,032	1,96532	,002	4,915	1	2530	,027	1,844

a. Predictors: (Constant), User friend count

b. Predictors: (Constant), User friend count, Squared_friendcount

c. Dependent Variable: Recommendation rate

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	309,018	1	309,018	79,882	,000[b]
	Residual	9791,019	2531	3,868		
	Total	10100,037	2532			
2	Regression	328,001	2	164,000	42,460	,000[c]
	Residual	9772,037	2530	3,862		
	Total	10100,037	2532			

a. Dependent Variable: Recommendation rate

b. Predictors: (Constant), User friend count

c. Predictors: (Constant), User friend count, Squared_friendcount

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	,386	,042		9,105	,000
	User friend count	,001	,000	,175	8,938	,000
2	(Constant)	,346	,046		7,503	,000
	User friend count	,001	,000	,275	5,595	,000
	Squared_friendcount	,000	,000	-,109	-2,217	,027

a. Dependent Variable: Recommendation rate

Table 3.2: Linear regression II, N = 2561

N = 3.144

Model Summary[c]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	,154[a]	,024	,023	1,99809	,024	75,523	1	3105	,000	
2	,160[b]	,026	,025	1,99650	,002	5,952	1	3104	,015	1,869

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	301,517	1	301,517	75,523	,000[b]
	Residual	12396,325	3105	3,992		
	Total	12697,842	3106			
2	Regression	325,242	2	162,621	40,798	,000[c]
	Residual	12372,600	3104	3,986		
	Total	12697,842	3106			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	,430	,039		10,972	,000	,353	,507
	User friend count	,001	,000	,154	8,690	,000	,001	,001
2	(Constant)	,387	,043		9,019	,000	,303	,471
	User friend count	,001	,000	,249	5,812	,000	,001	,002
	Squared_friendcount	,000	,000	-,105	-2,440	,015	,000	,000

Table 3.3: Linear regression III, N = 3144

H4: Multiple regression analysis song count and nationality

Excluded outliers with the Mahalanobis function

N = 2.061

Model Summary[c]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	,238[a]	,057	,056	2,37907	,057	122,418	1	2039	,000	
2	,288[b]	,083	,073	2,35812	,026	2,733	21	2018	,000	1,903

a. Predictors: (Constant), centred_playcount

b. Predictors: (Constant), centred_playcount, interaction1_italy, interaction1_australia, interaction1_lithuania, interaction1_ukraine, interaction1_spain, interaction1_chile, interaction1_france, interaction1_netherlands, interaction1_mexico, interaction1_finland, interaction1_japan, interaction1_indonesia, interaction1_sweden, interaction1_turkey, interaction1_canada, interaction1_russia, interaction1_poland, interaction1_UK, interaction1_germany, interaction1_brazil, interaction1_US

c. Dependent Variable: Recommendation rate

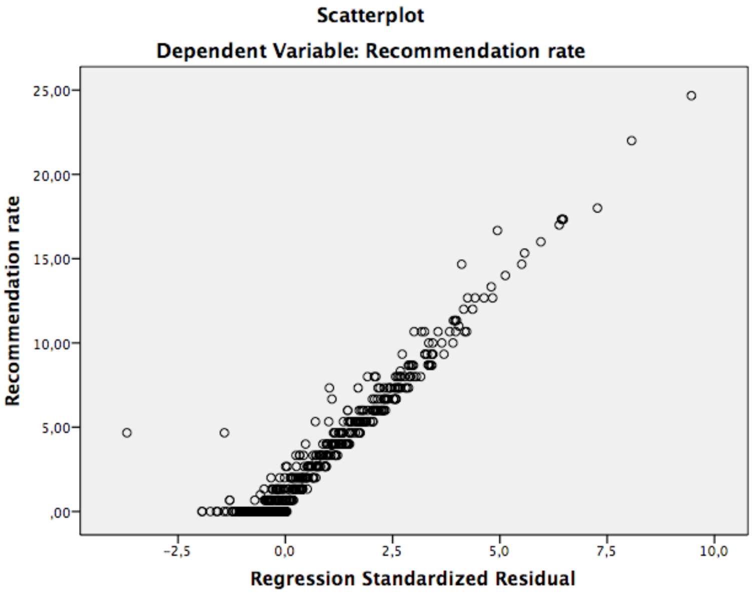
ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	692,882	1	692,882	122,418	,000[b]
	Residual	11540,671	2039	5,660		
	Total	12233,553	2040			
2	Regression	1012,041	22	46,002	8,273	,000[c]
	Residual	11221,512	2018	5,561		
	Total	12233,553	2040			

a. Dependent Variable: Recommendation rate

b. Predictors: (Constant), centred_playcount

c. Predictors: (Constant), centred_playcount, interaction1_italy, interaction1_australia, interaction1_lithuania, interaction1_ukraine, interaction1_spain, interaction1_chile, interaction1_france, interaction1_netherlands, interaction1_mexico, interaction1_finland, interaction1_japan, interaction1_indonesia, interaction1_sweden, interaction1_turkey, interaction1_canada, interaction1_russia, interaction1_poland, interaction1_UK, interaction1_germany, interaction1_brazil, interaction1_US



Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	,953	,053		17,933	,000
	centred_playcount	8,742E-006	,000	,238	11,064	,000
2	(Constant)	,947	,055		17,212	,000
	centred_playcount	7,620E-006	,000	,207	5,433	,000
	interaction1_US	5,865E-006	,000	,066	2,492	,013
	interaction1_brazil	,000	,000	-,038	-1,553	,120
	interaction1_UK	7,627E-006	,000	,056	2,378	,018
	interaction1_russia	8,777E-006	,000	,044	1,954	,051
	interaction1_indonesia	1,888E-006	,000	,008	,346	,729
	interaction1_poland	,000	,000	-,002	-,098	,922
	interaction1_germany	,000	,000	-,033	-1,378	,168
	interaction1_canada	,000	,000	-,039	-1,753	,080
	interaction1_finland	,000	,000	-,029	-1,329	,184
	interaction1_netherlands	3,200E-006	,000	,009	,415	,678
	interaction1_turkey	6,833E-006	,000	,027	1,229	,219
	interaction1_ukraine	3,733E-006	,000	,006	,302	,762
	interaction1_sweden	1,942E-006	,000	,008	,343	,731
	interaction1_italy	,000	,000	-,001	-,038	,969
	interaction1_japan	6,303E-007	,000	,002	,105	,916
	interaction1_australia	,000	,000	-,021	-,976	,329
	interaction1_spain	,000	,000	-,019	-,872	,383
	interaction1_france	1,383E-005	,000	,038	1,739	,082
	interaction1_mexico	,000	,000	-,036	-1,670	,095
	interaction1_lithuania	,000	,000	-,015	-,696	,487
	interaction1_chile	4,058E-005	,000	,089	4,116	,000

a. Dependent Variable: Recommendation rate

Table 4.1: Multiple regression I, N = 2061

N = 2.561

Model Summary[c]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,210[a]	,044	,044	1,93432	,044	116,209	1	2518	,000	
2	,264[b]	,070	,062	1,91612	,026	3,288	21	2497	,000	1,941

a. Predictors: (Constant), Centred_songplaycount

b. Predictors: (Constant), Centred_songplaycount, interaction1_Lithuania, interaction1_Italy, interaction1_Ukraine, interaction1_Spain, interaction1_Australia, interaction1_France, interaction1_Mexico, interaction1_Netherlands, interaction1_Chile, interaction1_Indonesia, interaction1_Finland, interaction1_Turkey, interaction1_Sweden, interaction1_Japan, interaction1_Canada, interaction1_Poland, interaction1_Russia, interaction1_UK, interaction1_Germany, interaction1_US, interaction1_Brazil

c. Dependent Variable: Recommendation rate

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	434,805	1	434,805	116,209	,000[b]
	Residual	9421,312	2518	3,742		
	Total	9856,117	2519			
2	Regression	688,327	22	31,288	8,522	,000[c]
	Residual	9167,790	2497	3,672		
	Total	9856,117	2519			

a. Dependent Variable: Recommendation rate

b. Predictors: (Constant), Centred_songplaycount

c. Predictors: (Constant), Centred_songplaycount, interaction1_Lithuania, interaction1_Italy, interaction1_Ukraine, interaction1_Spain, interaction1_Australia, interaction1_France, interaction1_Mexico, interaction1_Netherlands, interaction1_Chile, interaction1_Indonesia, interaction1_Finland, interaction1_Turkey, interaction1_Sweden, interaction1_Japan, interaction1_Canada, interaction1_Poland, interaction1_Russia, interaction1_UK, interaction1_Germany, interaction1_US, interaction1_Brazil

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	,597	,039		15,305	,000
	Centred_songplaycount	5,800E-006	,000	,210	10,780	,000
2	(Constant)	,579	,041		14,193	,000
	Centred_songplaycount	4,636E-006	,000	,168	5,177	,000
	interaction1_US	7,978E-006	,000	,099	4,439	,000
	interaction1_Brazil	,000	,000	-,040	-1,747	,081
	interaction1_UK	7,240E-006	,000	,064	3,056	,002
	interaction1_Russia	2,048E-006	,000	,017	,812	,417
	interaction1_Indonesia	3,245E-007	,000	,001	,076	,940
	interaction1_Poland	9,409E-007	,000	,007	,339	,735
	interaction1_Germany	,000	,000	-,017	-,821	,412
	interaction1_Canada	,000	,000	-,036	-1,783	,075
	interaction1_Finland	,000	,000	-,019	-,983	,326
	interaction1_Netherlands	1,112E-006	,000	,004	,216	,829
	interaction1_Turkey	1,023E-005	,000	,046	2,313	,021
	interaction1_Ukraine	2,554E-006	,000	,005	,270	,787
	interaction1_Sweden	5,890E-006	,000	,026	1,304	,192
	interaction1_Italy	,000	,000	-,005	-,236	,814
	interaction1_Japan	8,893E-008	,000	,000	,023	,981
	interaction1_Australia	,000	,000	-,022	-1,153	,249
	interaction1_Spain	,000	,000	-,013	-,690	,490
	interaction1_France	1,647E-005	,000	,052	2,666	,008
	interaction1_Mexico	,000	,000	-,027	-1,386	,166
	interaction1_Lithuania	,000	,000	-,010	-,509	,611
	interaction1_Chile	1,367E-005	,000	,052	2,652	,008

a. Dependent Variable: Recommendation rate

Table 4.2: Multiple regression II, N = 2561

N = 3.144

Model Summary[c]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	,186[a]	,035	,034	1,99198	,035	111,384	1	3101	,000	
2	,233[b]	,054	,048	1,97818	,020	3,069	21	3080	,000	1,960

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	441,971	1	441,971	111,384	,000[b]
	Residual	12304,766	3101	3,968		
	Total	12746,737	3102			
2	Regression	694,150	22	31,552	8,063	,000[c]
	Residual	12052,586	3080	3,913		
	Total	12746,737	3102			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	,630	,036		17,435	,000	,559	,701
	Centred_songplaycount	5,825E-006	,000	,186	10,554	,000	,000	,000
2	(Constant)	,618	,037		16,489	,000	,545	,692
	Centred_songplaycount	4,820E-006	,000	,154	5,273	,000	,000	,000
	interaction1_US	7,664E-006	,000	,084	4,152	,000	,000	,000
	interaction1_Brazil	,000	,000	-,038	-1,875	,061	,000	,000
	interaction1_UK	7,477E-006	,000	,058	3,070	,002	,000	,000
	interaction1_Russia	1,465E-006	,000	,011	,565	,572	,000	,000
	interaction1_Indonesia	9,317E-007	,000	,004	,212	,832	,000	,000
	interaction1_Poland	7,809E-007	,000	,005	,274	,784	,000	,000
	interaction1_Germany	,000	,000	-,018	-,954	,340	,000	,000
	interaction1_Canada	,000	,000	-,034	-1,871	,061	,000	,000
	interaction1_Finland	,000	,000	-,018	-1,034	,301	,000	,000
	interaction1_Netherlands	2,341E-006	,000	,008	,444	,657	,000	,000
	interaction1_Turkey	1,007E-005	,000	,039	2,208	,027	,000	,000
	interaction1_Ukraine	3,147E-006	,000	,006	,324	,746	,000	,000
	interaction1_Sweden	5,485E-006	,000	,021	1,178	,239	,000	,000
	interaction1_Italy	,000	,000	-,003	-,176	,860	,000	,000
	interaction1_Japan	,000	,000	-,001	-,065	,948	,000	,000
	interaction1_Australia	,000	,000	-,019	-1,100	,271	,000	,000
	interaction1_Spain	,000	,000	-,012	-,677	,498	,000	,000
	interaction1_France	1,502E-005	,000	,042	2,366	,018	,000	,000
	interaction1_Mexico	,000	,000	-,024	-1,365	,172	,000	,000
	interaction1_Lithuania	,000	,000	-,009	-,504	,614	,000	,000
	interaction1_Chile	1,287E-005	,000	,043	2,426	,015	,000	,000

Table 4.3: Multiple regression III, N = 3144

H5: Multiple regression analysis song count and music genre

Excluded outliers with the Mahalanobis function

N = 2.061

Model Summary[c]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	,238[a]	,057	,056	2,37907	,057	122,418	1	2039	,000	
2	,292[b]	,085	,078	2,35115	,029	4,248	15	2024	,000	1,892

a. Predictors: (Constant), centred_playcount

b. Predictors: (Constant), centred_playcount, interaction1_noise, interaction1_hardcore, interaction1_folk, interaction1_punk, interaction1_instrumental, interaction1_jazz, interaction1_japanese, interaction1_classical, interaction1_live, interaction1_hiphop, interaction1_metal, interaction1_pop, interaction1_rock, interaction1_indie, interaction1_electronic

c. Dependent Variable: Recommendation rate

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	692,882	1	692,882	122,418	,000[b]
	Residual	11540,671	2039	5,660		
	Total	12233,553	2040			
2	Regression	1045,114	16	65,320	11,816	,000[c]
	Residual	11188,438	2024	5,528		
	Total	12233,553	2040			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	,953	,053		17,933	,000
	centred_playcount	8,742E-006	,000	,238	11,064	,000
2	(Constant)	,908	,054		16,914	,000
	centred_playcount	6,041E-006	,000	,164	6,178	,000
	interaction1_indie	1,987E-005	,000	,127	5,731	,000
	interaction1_electronic	1,061E-005	,000	,075	3,326	,001
	interaction1_pop	9,795E-006	,000	,052	2,361	,018
	interaction1_rock	1,366E-005	,000	,077	3,510	,000
	interaction1_metal	,000	,000	-,017	-,796	,426
	interaction1_instrumental	,000	,000	-,006	-,266	,790
	interaction1_live	2,405E-006	,000	,009	,403	,687
	interaction1_hiphop	7,912E-006	,000	,034	1,587	,113
	interaction1_punk	,000	,000	-,010	-,482	,630
	interaction1_folk	,000	,000	-,019	-,870	,384
	interaction1_jazz	8,316E-006	,000	,023	1,058	,290
	interaction1_classical	,000	,000	-,011	-,501	,616
	interaction1_japanese	,000	,000	-,031	-1,421	,155
	interaction1_noise	2,905E-006	,000	,004	,184	,854
	interaction1_hardcore	,000	,000	-,016	-,744	,457

a. Dependent Variable: Recommendation rate

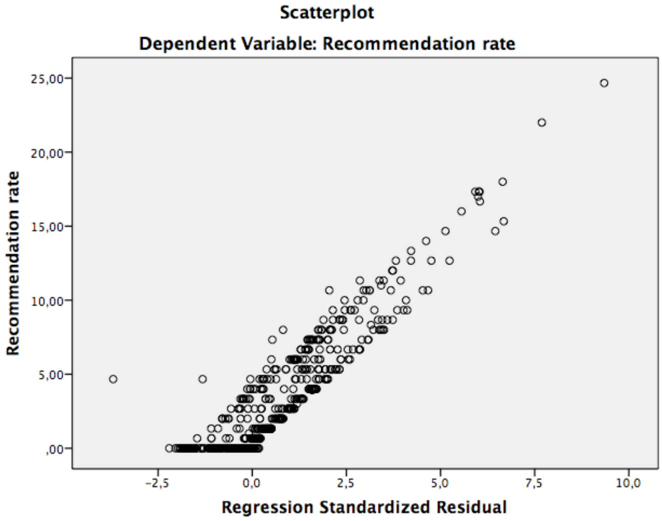


Table 5.1: Multiple regression I, N = 2061

N = 2.561

Model Summary[c]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	,210[a]	,044	,044	1,93432	,044	116,209	1	2518	,000	
2	,266[b]	,071	,065	1,91226	,027	5,174	14	2504	,000	1,940

a. Predictors: (Constant), Centred_songplaycount

b. Predictors: (Constant), Centred_songplaycount, interaction1_Noise, interaction1_Folk, interaction1_Hardcore, interaction1_Jazz, interaction1_Punk, interaction1_Classical, interaction1_Instrumental, interaction1_Live, interaction1_Hiphop, interaction1_Metal, interaction1_Rock, interaction1_Indie, interaction1_Electronic, interaction1_Pop

c. Dependent Variable: Recommendation rate

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	434,805	1	434,805	116,209	,000[b]
	Residual	9421,312	2518	3,742		
	Total	9856,117	2519			
2	Regression	699,676	15	46,645	12,756	,000[c]
	Residual	9156,441	2504	3,657		
	Total	9856,117	2519			

a. Dependent Variable: Recommendation rate

b. Predictors: (Constant), Centred_songplaycount

c. Predictors: (Constant), Centred_songplaycount, interaction1_Noise, interaction1_Folk, interaction1_Hardcore, interaction1_Jazz, interaction1_Punk, interaction1_Classical, interaction1_Instrumental, interaction1_Live, interaction1_Hiphop, interaction1_Metal, interaction1_Rock, interaction1_Indie, interaction1_Electronic, interaction1_Pop

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	,597	,039		15,305	,000
	Centred_songplaycount	5,800E-006	,000	,210	10,780	,000
2	(Constant)	,557	,040		13,989	,000
	Centred_songplaycount	3,976E-006	,000	,144	5,860	,000
	interaction1_Indie	1,458E-005	,000	,121	5,995	,000
	interaction1_Electronic	1,058E-005	,000	,091	4,527	,000
	interaction1_Pop	5,939E-007	,000	,006	,282	,778
	interaction1_Rock	9,935E-006	,000	,072	3,628	,000
	interaction1_Metal	,000	,000	-,025	-1,247	,213
	interaction1_Instrumental	,000	,000	-,016	-,810	,418
	interaction1_Live	4,429E-006	,000	,019	,988	,323
	interaction1_Hiphop	3,241E-006	,000	,021	1,059	,289
	interaction1_Punk	,000	,000	-,010	-,533	,594
	interaction1_Folk	,000	,000	-,011	-,571	,568
	interaction1_Jazz	1,007E-005	,000	,032	1,631	,103
	interaction1_Classical	1,049E-007	,000	,000	,020	,984
	interaction1_Noise	,000	,000	,000	-,008	,994
	interaction1_Hardcore	,000	,000	-,016	-,826	,409

a. Dependent Variable: Recommendation rate

Table 5.2: Multiple regression II, N = 2561

N = 3.144

Model Summary[c]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,186[a]	,035	,034	1,99198	,035	111,384	1	3101	,000	
2	,233[b]	,054	,050	1,97589	,020	4,623	14	3087	,000	1,959

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	441,971	1	441,971	111,384	,000[b]
	Residual	12304,766	3101	3,968		
	Total	12746,737	3102			
2	Regression	694,680	15	46,312	11,862	,000[c]
	Residual	12052,057	3087	3,904		
	Total	12746,737	3102			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95,0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	,630	,036		17,435	,000	,559	,701
	Centred_songplaycount	5,825E-006	,000	,186	10,554	,000	,000	,000
2	(Constant)	,600	,037		16,303	,000	,528	,672
	Centred_songplaycount	4,138E-006	,000	,132	5,953	,000	,000	,000
	interaction1_Indie	1,435E-005	,000	,104	5,726	,000	,000	,000
	interaction1_Electronic	9,857E-006	,000	,075	4,097	,000	,000	,000
	interaction1_Pop	2,414E-007	,000	,002	,112	,911	,000	,000
	interaction1_Rock	9,658E-006	,000	,062	3,424	,001	,000	,000
	interaction1_Metal	,000	,000	-,023	-1,249	,212	,000	,000
	interaction1_Instrumental	,000	,000	-,013	-,757	,449	,000	,000
	interaction1_Live	3,593E-006	,000	,014	,779	,436	,000	,000
	interaction1_Hiphop	2,955E-006	,000	,017	,937	,349	,000	,000
	interaction1_Punk	,000	,000	-,010	-,563	,574	,000	,000
	interaction1_Folk	,000	,000	-,010	-,585	,559	,000	,000
	interaction1_Jazz	1,009E-005	,000	,028	1,584	,113	,000	,000
	interaction1_Classical	,000	,000	-,001	-,031	,975	,000	,000
	interaction1_Noise	3,105E-007	,000	,001	,032	,974	,000	,000
	interaction1_Hardcore	,000	,000	-,015	-,839	,402	,000	,000

Table 5.3: Multiple regression III, N = 3144

Multiple regression analysis: Friend count and nationality

Excluded outliers with the Mahalanobis function

N = 2.061

Categorical dummy variables times a centred scale variable to create interaction effects.

Model Summary[d]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	,211[a]	,044	,044	2,39087	,044	94,563	1	2035	,000	
2	,234[b]	,055	,054	2,37871	,010	21,872	1	2034	,000	
3	,283[c]	,080	,070	2,35844	,026	2,672	21	2013	,000	1,933

a. Predictors: (Constant), centred_friendcount

b. Predictors: (Constant), centred_friendcount, squared_centred_friendcount

c. Predictors: (Constant), centred_friendcount, squared_centred_friendcount, interaction2_chile, interaction2_spain, interaction2_lithuania, interaction2_australia, interaction2_netherlands, interaction2_turkey, interaction2_mexico, interaction2_italy, interaction2_finland, interaction2_sweden, interaction2_germany, interaction2_canada, interaction2_poland, interaction2_ukraine, interaction2_indonesia, interaction2_japan, interaction2_russia, interaction2_UK, interaction2_france, interaction2_US, interaction2_brazil

d. Dependent Variable: Recommendation rate

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	540,551	1	540,551	94,563	,000[b]
	Residual	11632,633	2035	5,716		
	Total	12173,184	2036			
2	Regression	664,306	2	332,153	58,702	,000[c]
	Residual	11508,879	2034	5,658		
	Total	12173,184	2036			
3	Regression	976,417	23	42,453	7,632	,000[d]
	Residual	11196,767	2013	5,562		
	Total	12173,184	2036			

a. Dependent Variable: Recommendation rate

b. Predictors: (Constant), centred_friendcount

c. Predictors: (Constant), centred_friendcount, squared_centred_friendcount

d. Predictors: (Constant), centred_friendcount, squared_centred_friendcount, interaction2_chile, interaction2_spain, interaction2_lithuania, interaction2_australia, interaction2_netherlands, interaction2_turkey, interaction2_mexico, interaction2_italy, interaction2_finland, interaction2_sweden, interaction2_germany, interaction2_canada, interaction2_poland, interaction2_ukraine, interaction2_indonesia, interaction2_japan, interaction2_russia, interaction2_UK, interaction2_france, interaction2_US, interaction2_brazil

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	,997	,055		18,233	,000
	centred_friendcount	,001	,000	,211	9,724	,000
2	(Constant)	1,205	,070		17,165	,000
	centred_friendcount	,002	,000	,384	8,953	,000
	squared_centred_friend count	,000	,000	-,201	-4,677	,000
3	(Constant)	1,267	,073		17,245	,000
	centred_friendcount	,003	,000	,421	7,527	,000
	squared_centred_friend count	,000	,000	-,260	-5,404	,000
	interaction2_US	,000	,000	,020	,758	,449
	interaction2_brazil	,000	,000	-,017	-,638	,523
	interaction2_UK	,002	,001	,089	3,670	,000
	interaction2_russia	4,609E-005	,001	,002	,083	,934
	interaction2_indonesia	-,001	,001	-,030	-1,331	,183
	interaction2_poland	,001	,001	,019	,857	,392
	interaction2_germany	-,002	,001	-,034	-1,562	,118
	interaction2_canada	-,003	,001	-,047	-2,153	,031
	interaction2_finland	,001	,001	,013	,577	,564
	interaction2_netherlands	-,003	,002	-,032	-1,480	,139
	interaction2_turkey	,005	,002	,055	2,571	,010
	interaction2_ukraine	-,002	,001	-,045	-2,027	,043
	interaction2_sweden	-,001	,001	-,028	-1,286	,199
	interaction2_italy	-,003	,002	-,031	-1,416	,157
	interaction2_japan	-,001	,001	-,028	-1,200	,230
	interaction2_australia	,003	,003	,019	,872	,383
	interaction2_spain	,001	,004	,004	,174	,862
	interaction2_france	,002	,001	,059	2,432	,015
	interaction2_mexico	-,003	,002	-,026	-1,192	,233
	interaction2_lithuania	,002	,003	,014	,638	,523
	interaction2_chile	,001	,004	,003	,139	,889

a. Dependent Variable: Recommendation rate

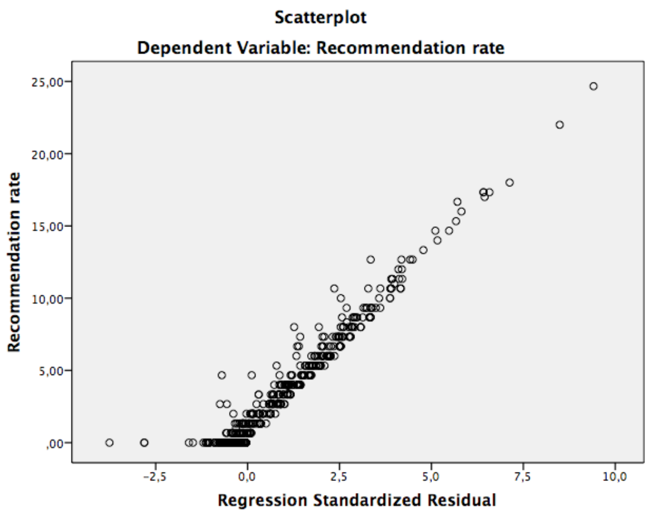


Table 4.4: Multiple regression IV, N = 2061

N = 2.561

Model Summary[d]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	,175[a]	,031	,030	1,96683	,031	79,882	1	2531	,000	
2	,180[b]	,032	,032	1,96532	,002	4,915	1	2530	,027	
3	,262[c]	,069	,060	1,93631	,036	4,637	21	2509	,000	1,892

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	309,018	1	309,018	79,882	,000[b]
	Residual	9791,019	2531	3,868		
	Total	10100,037	2532			
2	Regression	328,001	2	164,000	42,460	,000[c]
	Residual	9772,037	2530	3,862		
	Total	10100,037	2532			
3	Regression	693,060	23	30,133	8,037	,000[d]
	Residual	9406,978	2509	3,749		
	Total	10100,037	2532			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	,616	,040		15,334	,000
	Centred_friendcount	,001	,000	,175	8,938	,000
2	(Constant)	,690	,052		13,177	,000
	Centred_friendcount	,001	,000	,250	6,381	,000
	Centred_Squared_friendcount	,000	,000	-,087	-2,217	,027
3	(Constant)	,769	,054		14,160	,000
	Centred_friendcount	,001	,000	,305	6,259	,000
	Centred_Squared_friendcount	,000	,000	-,153	-3,633	,000
	interaction2_US	,000	,000	,036	1,583	,114
	interaction2_Brazil	-,001	,000	-,057	-2,183	,029
	interaction2_UK	,002	,000	,124	5,897	,000
	interaction2_Russia	,000	,000	-,015	-,705	,481
	interaction2_Indonesia	-,001	,001	-,020	-1,015	,310
	interaction2_Poland	,001	,001	,024	1,208	,227
	interaction2_Germany	-,002	,001	-,037	-1,876	,061
	interaction2_Canada	-,003	,001	-,043	-2,220	,026
	interaction2_Finland	,001	,001	,019	,969	,332
	interaction2_Netherlands	,000	,002	-,002	-,078	,938
	interaction2_Turkey	,005	,002	,059	3,067	,002
	interaction2_Ukraine	-,001	,001	-,035	-1,750	,080
	interaction2_Sweden	-,001	,001	-,026	-1,338	,181
	interaction2_Italy	-,002	,001	-,026	-1,326	,185
	interaction2_Japan	-,001	,001	-,030	-1,462	,144
	interaction2_Australia	,001	,002	,012	,632	,527
	interaction2_Spain	-,001	,003	-,006	-,314	,754
	interaction2_France	,002	,001	,065	3,086	,002
	interaction2_Mexico	-,002	,002	-,032	-1,637	,102
	interaction2_Lithuania	,002	,003	,010	,540	,589
	interaction2_Chile	,002	,003	,012	,647	,518

a. Dependent Variable: Recommendation rate

Table 4.5: Multiple regression V, N = 2561

N = 3.144

Model Summary[d]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	,154[a]	,024	,023	1,99809	,024	75,523	1	3105	,000	
2	,160[b]	,026	,025	1,99650	,002	5,952	1	3104	,015	
3	,221[c]	,049	,042	1,97918	,023	3,599	21	3083	,000	1,911

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	301,517	1	301,517	75,523	,000[b]
	Residual	12396,325	3105	3,992		
	Total	12697,842	3106			
2	Regression	325,242	2	162,621	40,798	,000[c]
	Residual	12372,600	3104	3,986		
	Total	12697,842	3106			
3	Regression	621,272	23	27,012	6,896	,000[d]
	Residual	12076,570	3083	3,917		
	Total	12697,842	3106			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	,645	,037		17,456	,000
	Centred_friendcount	,001	,000	,154	8,690	,000
2	(Constant)	,719	,048		15,073	,000
	Centred_friendcount	,001	,000	,225	6,596	,000
	Centred_Squared_friendcount	,000	,000	-,083	-2,440	,015
3	(Constant)	,781	,050		15,761	,000
	Centred_friendcount	,001	,000	,270	6,230	,000
	Centred_Squared_friendcount	,000	,000	-,134	-3,652	,000
	interaction2_US	,000	,000	,028	1,377	,169
	interaction2_Brazil	,000	,000	-,044	-1,829	,068
	interaction2_UK	,002	,000	,088	4,584	,000
	interaction2_Russia	,000	,000	-,012	-,604	,546
	interaction2_Indonesia	-,001	,001	-,014	-,791	,429
	interaction2_Poland	,001	,001	,022	1,237	,216
	interaction2_Germany	-,001	,001	-,028	-1,545	,123
	interaction2_Canada	-,002	,001	-,036	-2,035	,042
	interaction2_Finland	,001	,001	,015	,833	,405
	interaction2_Netherlands	-,002	,001	-,020	-1,130	,259
	interaction2_Turkey	,005	,002	,054	3,068	,002
	interaction2_Ukraine	-,001	,001	-,031	-1,679	,093
	interaction2_Sweden	-,001	,001	-,020	-1,104	,270
	interaction2_Italy	-,002	,001	-,022	-1,260	,208
	interaction2_Japan	-,001	,001	-,027	-1,472	,141
	interaction2_Australia	,002	,002	,015	,842	,400
	interaction2_Spain	-,001	,003	-,004	-,215	,830
	interaction2_France	,002	,001	,060	3,137	,002
	interaction2_Mexico	-,002	,001	-,025	-1,437	,151
	interaction2_Lithuania	,001	,003	,008	,454	,650
	interaction2_Chile	,000	,002	,003	,143	,886

Table 4.6: Multiple regression VI, N = 3144

Multiple regression analysis: Friend count and music genre

Excluded outliers with the Mahalanobis function

N = 2.061

Model Summary[d]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	,211[a]	,044	,044	2,39087	,044	94,563	1	2035	,000	
2	,234[b]	,055	,054	2,37871	,010	21,872	1	2034	,000	
3	,252[c]	,064	,056	2,37620	,009	1,287	15	2019	,202	1,917

a. Predictors: (Constant), centred_friendcount

b. Predictors: (Constant), centred_friendcount, squared_centred_friendcount

c. Predictors: (Constant), centred_friendcount, squared_centred_friendcount, interaction2_punk, interaction2_noise, interaction2_live, interaction2_hiphop, interaction2_folk, interaction2_classical, interaction2_hardcore, interaction2_jazz, interaction2_pop, interaction2_metal, interaction2_rock, interaction2_electronic, interaction2_japanese, interaction2_instrumental, interaction2_indie

d. Dependent Variable: Recommendation rate

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	540,551	1	540,551	94,563	,000[b]
	Residual	11632,633	2035	5,716		
	Total	12173,184	2036			
2	Regression	664,306	2	332,153	58,702	,000[c]
	Residual	11508,879	2034	5,658		
	Total	12173,184	2036			
3	Regression	773,267	17	45,486	8,056	,000[d]
	Residual	11399,917	2019	5,646		
	Total	12173,184	2036			

a. Dependent Variable: Recommendation rate

b. Predictors: (Constant), centred_friendcount

c. Predictors: (Constant), centred_friendcount, squared_centred_friendcount

d. Predictors: (Constant), centred_friendcount, squared_centred_friendcount, interaction2_punk, interaction2_noise, interaction2_live, interaction2_hiphop, interaction2_folk, interaction2_classical, interaction2_hardcore, interaction2_jazz, interaction2_pop, interaction2_metal, interaction2_rock, interaction2_electronic, interaction2_japanese, interaction2_instrumental, interaction2_indie

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	,997	,055		18,233	,000
	centred_friendcount	,001	,000	,211	9,724	,000
2	(Constant)	1,205	,070		17,165	,000
	centred_friendcount	,002	,000	,384	8,953	,000
	squared_centred_friend count	,000	,000	-,201	-4,677	,000
3	(Constant)	1,223	,072		17,057	,000
	centred_friendcount	,002	,000	,391	8,317	,000
	squared_centred_friend count	,000	,000	-,212	-4,609	,000
	interaction2_indie	,000	,001	,013	,551	,582
	interaction2_electronic	,001	,001	,047	2,104	,035
	interaction2_pop	-,001	,001	-,022	-1,025	,305
	interaction2_rock	-,001	,001	-,011	-,494	,622
	interaction2_metal	,000	,001	-,012	-,562	,574
	interaction2_instrumenta l	,001	,001	,024	1,057	,291
	interaction2_live	,003	,002	,037	1,697	,090
	interaction2_hiphop	,002	,002	,024	1,127	,260
	interaction2_punk	-,002	,003	-,016	-,743	,458
	interaction2_folk	-,001	,002	-,016	-,735	,463
	interaction2_jazz	-,001	,001	-,020	-,900	,368
	interaction2_classical	,001	,002	,013	,580	,562
	interaction2_japanese	-,001	,001	-,022	-,975	,330
	interaction2_noise	,001	,003	,008	,394	,694
	interaction2_hardcore	-,002	,001	-,041	-1,893	,058

a. Dependent Variable: Recommendation rate

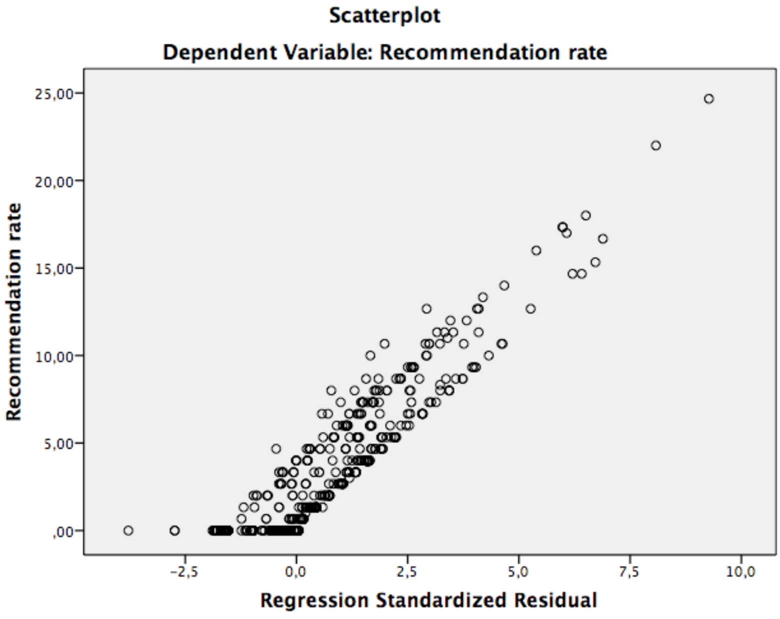


Table 5.4: Multiple regression IV, N = 2061

N = 2.561

Model Summary[d]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	,175[a]	,031	,030	1,96683	,031	79,882	1	2531	,000	
2	,180[b]	,032	,032	1,96532	,002	4,915	1	2530	,027	
3	,210[c]	,044	,038	1,95883	,012	2,198	14	2516	,006	1,844

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	309,018	1	309,018	79,882	,000[b]
	Residual	9791,019	2531	3,868		
	Total	10100,037	2532			
2	Regression	328,001	2	164,000	42,460	,000[c]
	Residual	9772,037	2530	3,862		
	Total	10100,037	2532			
3	Regression	446,083	16	27,880	7,266	,000[d]
	Residual	9653,955	2516	3,837		
	Total	10100,037	2532			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	,616	,040		15,334	,000
	Centred_friendcount	,001	,000	,175	8,938	,000
2	(Constant)	,690	,052		13,177	,000
	Centred_friendcount	,001	,000	,250	6,381	,000
	Centred_Squared_friendcount	,000	,000	-,087	-2,217	,027
3	(Constant)	,714	,053		13,469	,000
	Centred_friendcount	,001	,000	,263	6,323	,000
	Centred_Squared_friendcount	,000	,000	-,117	-2,905	,004
	interaction2_Indie	,001	,000	,037	1,844	,065
	interaction2_Electronic	,002	,000	,067	3,353	,001
	interaction2_Pop	-,001	,000	-,036	-1,816	,070
	interaction2_Rock	-,001	,001	-,028	-1,416	,157
	interaction2_Metal	,000	,001	-,012	-,617	,537
	interaction2_Instrumental	,001	,000	,033	1,650	,099
	interaction2_Live	,000	,001	,006	,290	,772
	interaction2_Hiphop	,002	,001	,025	1,267	,205
	interaction2_Punk	-,002	,002	-,017	-,888	,375
	interaction2_Folk	,000	,001	-,005	-,272	,786
	interaction2_Jazz	,000	,001	-,001	-,056	,956
	interaction2_Classical	,002	,001	,028	1,419	,156
	interaction2_Noise	,001	,002	,010	,524	,600
	interaction2_Hardcore	-,001	,001	-,031	-1,555	,120

a. Dependent Variable: Recommendation rate

Table 5.5: Multiple regression V, N = 2561

N = 3.144

Model Summary[d]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	,154[a]	,024	,023	1,99809	,024	75,523	1	3105	,000	
2	,160[b]	,026	,025	1,99650	,002	5,952	1	3104	,015	
3	,185[c]	,034	,029	1,99208	,009	1,985	14	3090	,016	1,863

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	301,517	1	301,517	75,523	,000[b]
	Residual	12396,325	3105	3,992		
	Total	12697,842	3106			
2	Regression	325,242	2	162,621	40,798	,000[c]
	Residual	12372,600	3104	3,986		
	Total	12697,842	3106			
3	Regression	435,504	16	27,219	6,859	,000[d]
	Residual	12262,338	3090	3,968		
	Total	12697,842	3106			

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	,645	,037		17,456	,000
	Centred_friendcount	,001	,000	,154	8,690	,000
2	(Constant)	,719	,048		15,073	,000
	Centred_friendcount	,001	,000	,225	6,596	,000
	Centred_Squared_friendcount	,000	,000	-,083	-2,440	,015
3	(Constant)	,734	,048		15,240	,000
	Centred_friendcount	,001	,000	,231	6,366	,000
	Centred_Squared_friendcount	,000	,000	-,098	-2,795	,005
	interaction2_Indie	,000	,000	,014	,769	,442
	interaction2_Electronic	,001	,000	,058	3,171	,002
	interaction2_Pop	-,001	,000	-,042	-2,271	,023
	interaction2_Rock	,000	,001	-,015	-,822	,411
	interaction2_Metal	,000	,001	-,007	-,414	,679
	interaction2_Instrumental	,001	,000	,031	1,688	,092
	interaction2_Live	,001	,001	,012	,651	,515
	interaction2_Hiphop	,002	,001	,024	1,338	,181
	interaction2_Punk	-,001	,002	-,010	-,544	,586
	interaction2_Folk	,000	,001	-,003	-,175	,861
	interaction2_Jazz	3,120E-005	,001	,001	,043	,966
	interaction2_Classical	,002	,001	,026	1,440	,150
	interaction2_Noise	2,799E-005	,002	,000	,018	,986
	interaction2_Hardcore	-,001	,001	-,029	-1,631	,103

Table 5.6: Multiple regression VI, N = 3144