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How Bands Grow:

An examination of patterns of competition in listening behaviour

Submission for the award of Masters by Research (Marketing)

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Abstract

For musicians to be successful, they need to understand who is listening, and how people are listening to their music. Practitioners claim that a band needs only 1000 true fans to be successful (Kelly 2008). In the context of the growing popularity of music streaming and the subsequent availability of millions of songs, understanding patterns of music consumption behaviour is more important than ever for musicians (Wlömert & Papies 2016).

Music literature has examined the links between music preferences and demographic and psychographic variables, and has generally found that differences exist e.g. white, middle-class males prefer Rock music (Greenberg et al. 2016; North & Hargreaves 2007c; Savage 2006). These findings suggest that some music competes separately to others, and that there are specific groups of listeners to whom an artist needs to appeal, as their preferences are isolated from the larger market. However, there is a potential overstatement of the differences in listener profiles given these studies have inconsistent findings and, in some instances, low correlations, or use unrepresentative student samples (e.g. Delsing et al. 2008; Greenberg et al. 2016; North 2010).

The marketing literature offers two empirical generalisations that can provide an understanding of how music competes. Firstly, the law of Duplication of Purchase (DoP) states that the level of customer sharing between two brands ('duplication') is directly proportional the penetration (size) of the brands (Goodhardt & Ehrenberg 1969). The Law generalises to a range of consumption contexts such as television channel and program viewing, radio station listening, entertainment and leisure, automobiles and consumer packaged goods (Bandyopadhyay & Martell 2007; Dawes et al. 2009; Goodhardt 1966; Lam & Ozorio 2013; Lees & Wright 2013). The second empirical generalisation is that the buyer profiles of competing brands seldom differ (Hammond et al. 1996). Studies have found that this pattern holds for brands in consumer-packaged goods, services, clothing, and media (Barwise & Ehrenberg 1988; Lees et al. 2016; Patrick et al. 2016; Uncles et al. 2012).

This thesis applies these two empirical generalisations to online music listening in order to test some of the findings in the music literature. Study One empirically tests whether brand size is the main determinant of competition between genres, artists, albums and songs and if genres compete separately in different submarkets. Study Two examines whether different music genres compete by appealing to a distinct segment of listeners. Study Three, as an extension of Study Two, investigates the influence of age and a 'nostalgia' effect on music listening preferences.

Objective of Thesis

This research examines how different music competes. Specifically, it investigates the extent to which various music genres, artists, albums and songs' listener bases overlap. A high degree of overlap would indicate that these music 'brands' do not compete by serving a unique segment of the market and that listening is eclectic. Secondly, it explores whether the listeners of genres are similar in their demographic or

psychographic profiles. Additionally, this research considers the degree to which music preferences may be influenced further by age and specifically nostalgia, by replicating the seminal research (Holbrook & Schindler 1989). That is, whether preferences for music is formed during a critical period of maximum sensitivity.

Data

This thesis uses two main data sources. Firstly, Study One uses four large datasets of actual music listening behaviour. The data spans more than a year of listening for 27,000+ users of Last.fm, an opt-in listening tracking service. Analysis of the largest 99 'brands' and an aggregated 'all other' brand was undertaken for genres, artists, albums and songs. The analysis is undertaken on four behavioural datasets, and one secondary claimed behavioural dataset (Study Two primary survey data). This is a many sets of data approach. To examine the demographic and psychographic listener profiles of genres, Study Two uses survey data from a sample of 1,036 respondents, nationally representative of the United States. Participants completed a Big Five Inventory 10-item personality scale (Rammstedt & John 2007), music media usage, motivations for music listening, past weekly listening of 13 music genres, and a range of demographic questions. The same survey data is also used in Study Three to examine the influence of age and nostalgia on the development of music preferences.

Main Findings

Study One: Music listening follows the Law of Duplication of Purchase

Study One finds that the degree of overlap of the listener bases for music genres, artists, albums and songs follows brand size, which is consistent with the law of Duplication of Purchase (Goodhardt & Ehrenberg 1969). That is, larger music brands gain more listeners from smaller music brands. This is shown by the close fit of music listening to DoP theoretical sharing measures (overall average: Pearson's correlation = 0.92, mean absolute deviation = 4, mean absolute percentage error = 14%). While oversharing of listeners is observed for sub-genres from the same meta genre (e.g. Soft Rock overshares with Classic Rock as they are both Rock genres), sharing between larger genre groupings is as predicted, with no partitioning occurring (e.g. listeners of Heavy Metal are as likely as listeners of Classical music or Hip-Hop/Rap to also listen to Pop music).

Study Two: Genres attract similar demographic and psychographic listeners

Study Two finds that the demographic (e.g. age, gender, ethnicity, social class) and psychographic (e.g. personality trait, motivation) listener profiles of genres are similar. This is demonstrated by the low overall mean absolute deviation of 3 percentage points (average for all demographics, psychographics and media usage variables). However, more differences are observed for age, particularly among older listeners (aged 55+). This older age group are overrepresented listeners of Country, Classical, Jazz, Blues and Folk and underrepresented listeners of Hip-Hop/Rap, Metal, Indie/Alternative, and Electronica/Dance.

Study Three: Preferences for popular music reflect tastes acquired during adolescence

Study Three finds that preferences for popular music peaks when an individual is around 14 to 15.5 years old, that is, during early-to-mid-adolescence. Therefore, this research finds support for the seminal study (Holbrook & Schindler 1989). However, this is nearly a 10 year decrease in age from the original study. Generational cohort analysis reveals a gradually decreasing age peak from the oldest to youngest cohort. Consequently, a lowering in the age peak may be attributable to increased music exposure at a younger age, due to the proliferation of a range of technologies. This finding may also explain some of the larger differences observed for age in Study Two.

Contributions and Future Research

This thesis extends the scope of DoP and brand user-profile research to include music listening. Consequently, this thesis contributes to the body of knowledge by demonstrating that music brands are not a boundary condition of these two marketing laws. Evidence that conflicts with music preference studies is also found, which is explained by, and demonstrates the importance of, considering managerially significant rather than statistically significant differences in research, and in music listening. Given that genres, artists, albums and songs compete on the basis of penetration, and genres rarely attract a unique demographic or psychographic listener, music marketers should focus on amassing a broad fan base rather than a few loyal fans (Kelly 2008). Furthermore, knowledge of the law of DoP enables music stakeholders to benchmark a music brand's performance and understand market norms. Replication confirms the effect of nostalgia and age on the development of popular music preferences (Holbrook & Schindler 1989). Knowledge of this nostalgia effect enables retailers and advertisers to optimally select music for their intended age demographic. Future research should examine the listener profiles of competing artists within and across genres, rather than only between genres.

Declaration

This thesis presents work carried out by myself and does not incorporate, without any acknowledgment, any material previously submitted for a degree or diploma in any university; to the best of my knowledge, it does not contain any materials previously published or written by another person except where due reference is made in text; and all substantive contributions by others to the work presented, including jointly authored publications, is clearly acknowledged.



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Callum Davies
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1. Introduction

1.1. Research background

Music listening is a highly popular and prevalent activity. Americans are estimated to spend 32 hours a week listening to music, which is around four-and-a-half hours a day (Nielsen 2017). According to recent industry reports, there are 255 million paid subscribers to music streaming services and streaming now accounts for 37 percent of the US $19.1 billion-dollar music industry (International Federation of the Phonographic Industry 2019b). Digital streaming technologies provide unprecedented access to millions of songs on demand (Krause et al. 2015), which can make finding the right music to listen to an overwhelming choice. Conversely, from an artist's perspective, their songs must compete with millions of others for listeners. Record companies are investing more than a third of their global revenue (US$5.8 B) on new artist scouting and marketing activities, traditionally known as Artists & Repertoire, or A&R (International Federation of the Phonographic Industry 2019b). Consequently, there is value in understanding how music competes for listeners, in order to maximise an artist's growth potential and profitability for music stakeholders.

1.2. Key literature

Prior research on music listening has investigated its psychological and physiological functions, contexts and environments for consumption, and device and personal music library management (e.g. Boal-Palheiros & Hargreaves 2001; Haake 2011; Hagen 2015; Kim & André 2008; Krause et al. 2015; Lesiuk 2005; Lim et al. 2015; Menon & Levitin 2005; Morris & Powers 2015; Salimpoor et al. 2009; Särkämö et al. 2008; Schäfer et al. 2013; Thoma et al. 2012). However, the relationship between demographic and psychographic variables and music preference is an area that has received particular attention. General findings are that music preferences differ by demographic and psychographic variables (e.g. Greenberg et al. 2016; Rentfrow & Gosling 2003). For example, Savage (2006) demographically profiles Rock listeners as white, middle-class, and male, while Country's listeners are old, low in educational achievement and mostly from an ethnic minority background. The link between personality traits and music preference has received considerable attention. Some studies find correlations between the Big Five personality traits and music preferences (e.g. George et al. 2007; Zweigenhaft 2008). For example, extraverts are more inclined to enjoy Pop music (Rawlings & Ciancarelli 1997). On the premise of distinct demographic and psychographic differences in music preference, music might compete in a segmented market, with different styles or genres attracting a unique listening base.

However, there are a number of limitations of music preference studies. Greenberg et al. (2016) finds that personality predicts music preference far beyond demographic variables. Conversely, North (2010) finds that music preference is more closely related to demographic variables, especially age. There is also overstatement of findings. For example, correlations between personality and music preferences are generally weak (i.e. $r < .30$) (e.g. Dunn et al. 2012; George et al. 2007; Rentfrow & Gosling 2003; Zweigenhaft 2008). Findings that demographic and psychographic variables only explain between two and five percent of the variance in music preference casts further

doubt over the generalisability of some findings (Baur et al. 2012; North 2010). Inconsistent findings and low correlations suggest that demographic or psychographic variables may have a negligible influence on music preference. Therefore, further investigation is merited.

The marketing literature offers two empirical generalisations that provide an understanding of how brands compete. Firstly, the law of Duplication of Purchase (DoP) states that the level of customer sharing (or duplication) between two brands is directly proportional to the penetration (size) of the brands (Goodhardt & Ehrenberg 1969). That is, brands are bought in line with size, where many of a brand's customers also buy the larger brands but few also buy small brands. A useful application of the law of DoP is that any brands that share more or fewer customers than expected, indicates the presence of a separate submarket or partition (Sharp & Sharp 1997). This reveals which brands are functionally similar, and considered substitutable by consumers (Romaniuk & Dawes 2005). When markets are partitioned, a grouping of brands shares more customers with each other and fewer with brands outside of the grouping, such as caffeinated and decaffeinated coffee brands (Dawes 2016; Kalwani & Morrison 1977). A key implication of the law of DoP is that brands compete head-on in a largely unsegmented mass market (Dawes 2008; Ehrenberg et al. 2004). This contrasts with music preference studies, which report demographic and psychographic music preference segments. To date, the law of DoP has been applied to a number of consumption behaviours such as television channel and program viewing, radio station listening, automobile purchasing and tourist destinations (e.g. Colombo et al. 2000; Dawes et al. 2009; Goodhardt 1966; Goodhardt & Ehrenberg 1969; Lees & Wright 2013). However, the generalisability of the Law has not yet been examined for music listening in an online context.

The online listening context presents a number of roadblocks that may disrupt the application of the law of DoP, such that the Law may not apply. Most notably, online music listening is subject to the use of music recommendation systems and auto play functions, which can provide highly targeted suggestions to individual listeners (Domingues et al. 2013). These systems are considered successful in alleviating the overwhelming choice of music available (Ricci et al. 2015). Recommender systems or features may disrupt some of the key assumptions underpinning the Dirichlet model that describes the law of DoP, especially that of "as-if-random" purchasing (Goodhardt et al. 1984). Should their impact be substantial, online music listening may be a boundary condition of the law of DoP.

Therefore, Study One addresses the research questions:

RQ1a: Does music listening follow the law of Duplication of Purchase for (a) genre, (b) album, (c) artist, and (d) songs?

RQ1b: Is there evidence of any partitioning between genres?

The second empirical generalisation is that competing brands attract a very similar type of customer (Hammond et al. 1996; Uncles et al. 2012). This pattern holds across a number of different contexts such as consumer packaged goods, services, fashion and television channels and programs (e.g. Barwise & Ehrenberg 1988; Bennett et al. 2016; Kennedy et al. 2000; Lees et al. 2016). The interpretation of results used in the marketing literature focuses on differences of managerial significance rather than statistical significance (e.g. Kennedy et al. 2014; Uncles et al. 2012). That is, the interpretation of results focuses on differences that are actionable in practice and therefore useful to marketing practitioners (Kennedy et al. 2014). The research questions considered in Study Two of this thesis are:

RQ2a: Do music genre listener-profiles differ by demographic or usage variables?

RQ2b: Do music genre listener-profiles differ by psychographic variables?

Studies indicate that age may be a more significant influence on music preference than other demographic or psychographic variables (e.g. North 2010; Savage 2006). The effect of nostalgia, as an extension of age, has been further explored by studies (e.g. Hemming 2013; Holbrook & Schindler 1989). The seminal study, conducted 30 years ago, found that preferences for popular music follow an inverted U-shaped curve, peaking when an individual is around 23.5 years old (Holbrook & Schindler 1989). This period of the formulation of popular music preference is referred to as late adolescence or early adulthood. Upon replication, a conflicting age peak of 8.6 was found (Hemming 2013). Hemming's (2013) replication study asserts that no empirical support for the seminal study's findings remains. Re-examination of the replication data uncovered a number of limitations pertaining to the method of analysis, such as the inclusion of unreliable observations (Holbrook & Schindler 2013). Ongoing debate and inconsistent findings underline the need for further examination. Therefore, Study Three of this thesis addresses the following question:

RQ3: Do preferences for popular music peak during the period of late adolescence or early adulthood?

1.3. Research Approach

This thesis adopts a differentiated replication design and many sets of data (MSoD) approach in order to strengthen two empirical generalisations (EGs): (1) the law of Duplication of Purchase (Goodhardt & Ehrenberg 1969) & (2) the customer profiles of competing brands seldom differs (Hammond et al. 1996; Uncles et al. 2012). An empirical generalisation is a relationship between multiple variables that has been observed to recur across varied conditions (Uncles & Wright 2004). This thesis applies known EGs to a new condition in music listening. Therefore, it seeks to strengthen knowledge of the conditions under which the EGs apply, or fail to apply.

Many sets of data are crucial in establishing EGs (Barwise 1995; Lindsay & Ehrenberg 1993). A MSoD approach focuses on identifying significant sameness, which is whether the prior model holds across different data, rather than identifying statistical significance (Ehrenberg 1990). This is actioned in Study One through the use of 4 sets of music listening data in order to test the stability of the law of DoP. This thesis also

uses a differentiated replication design, which is a duplication or extension of a previously published study but with varied conditions (i.e. context, research team, time). Both MSoD and differentiated replication are fundamental in establishing and strengthening EGs (Ehrenberg 1990, 1995). Studies Two and Three are differentiated replications seeking to extend the generalisability of earlier studies (e.g. Holbrook & Schindler 1989; Uncles et al. 2012). Therefore, Studies Two and Three contribute to the many sets of data already established in the literature.

1.4. Method

Study One uses four behavioural datasets collected from Last.fm, which is an opt-in online music aggregator and recommender service. Last.fm records the music listening of users across a number of online music streaming services (e.g. Spotify, Apple Music, YouTube) and can include offline music listening (e.g. Compact Disc, personal iTunes libraries). The four datasets comprise a total of 26,000 music listeners. DoP analysis was conducted for the largest 99 genres, artists, albums and songs (separately) and an aggregated 'all other'. A fifth merged dataset contributes four additional analyses. Survey data of claimed listening of 13 genres adds an extra analysis (primary Study Two data). A total of 21 DoP analyses were conducted.

Study Two data comes from a nationally representative survey of the United States (n=1,036). The survey was conducted in February 2019 and captured demographic variables (e.g., age, gender, ethnicity, social class), usage variables (media used for music consumption), psychographic variables (e.g., personality, music listening motivations) and past weekly listening of 13 central genres. Crosstabulations between demographic, psychographic, usage variables and actively consumed genres were calculated in order to determine each genre's listener profile. Deviations from the 'average' genre profile were calculated to assess the degree of similarity, in line with generalisable brand user-profile research (e.g. Hammond et al. 1996).

Data for Study Three comes from the same US sample (n=1,036) used in Study Two. To assess the generalisability of Holbrook and Schindler (1989) findings, liking assessed on a 10-point scale for 34, 30-second excerpts of selected Billboard top ten songs from 1950 to 2016 were measured. These scores were standardised to form the dependent variable while respondents' age at the time each song feature in the Billboard charts form the independent variable. Analysis was then conducted using multiple regression models.

1.5. Findings

Study One finds that music competition at the genre, artist, album, and song level, closely follows the law of DoP. That is, the level of sharing between any pair of music "brands" is directly proportional to the "brands'" penetration. This is demonstrated by the close fit between the observed and theoretical sharing levels. The average test of fit measures across 21 analyses find an average Pearson's correlation between penetration and average sharing of 0.98, mean absolute deviations of 4, and a mean absolute percentage error of 14%, which indicates large similarity between observed and theoretical sharing. Submarket and partition analysis at the genre level reveals that

while sub-genres share more listeners with other sub-genres that belong to the same 'meta' genre (e.g., Soft Rock listeners are more likely to also listen to Classic Rock as both are 'Rock' sub-genres), listening between larger genre groupings is as expected, with no partitioning observed (e.g. listeners of Heavy Metal or Classical still also listen to Pop).

Study Two reveals that the listening bases of 13 core music genres are more similar than different for demographic, psychographic and media usage variables. This is shown by the low mean absolute deviation (MAD) of 3 across all variables. Some notable and larger deviations (±10 percentage points) were observed for age. Most of these deviations occur among listeners aged 55 or older. In particular, this age group is underrepresented in the listener bases of Hip-Hop/Rap and Electronica/Dance and overrepresented as listeners of Country, Classical, Jazz, Folk and Blues. Aside from this age group, genres rarely attract a different demographic, psychographic and media usage type of listener.

Study Three finds that preferences for popular music peaks during adolescence, which is supportive of Holbrook and Schindler's (1989) original findings. Preferences for popular music peak when an individual is around 14 to 15.5 years old, that is, early-to-mid adolescence. This differs from the initial age of 23.5 which was described as late adolescence or early adulthood (Holbrook & Schindler 1989). The lower age found in this research might be attributed to increased music exposure at younger age, especially to popular music. The finding that popular music preferences peak during a period of adolescence, may also explain the larger differences in the genre listener composition for age found in Study Two.

1.6. Contributions to Theory

This thesis extends the generalisability of the law of DoP to include music listening of genres, artists, albums and songs in the previously unexplored online context. Secondly, this thesis demonstrates that genres do not attract a dissimilar demographic, psychographic or media usage listening base. Together, these findings extend the known conditions for two empirical generalisations (law of DoP and the customer profiles of competing brands seldom differs) by revealing that music listening, at least at the genre level, is not a boundary condition.

When using a managerially significant viewpoint, Study Two suggests that previous findings in the music literature may be overstated. Through replication, Study Three confirms the existence of Holbrook and Schindler's (1989) nostalgia effect in the development of popular music preferences. However, the age that popular music preferences are developed occurs during earlier adolescence, when an individual is between 14 and 15.5 years old. This finding contradicts Hemming's (2013) replication which finds an age of 8.6.

1.7. Contributions to Practice

The findings of this thesis are of importance to music stakeholders concerned with the promotion of music brands (e.g., artists, music marketers/labels, streaming

services). Knowledge that music listening follows the law of DoP provides realistic benchmarks for brand growth and an understanding of market norms. In addition, the finding that genre listener profiles are more similar than different indicates the importance of a mass marketing strategy. For example, that listeners of Classical music are similar to listeners of Rock, demonstrates the limits of demographic and psychographic targeting, at least at the genre level. This similarity is largely caused by eclectic tastes, such that listening to both Classical and Rock genres results in a listener appearing in both genre's profiles. Thus, the profiles of Classical and Rock are more similar than different. The similarity may also be a product of statistics, in that the more popular genres contribute a larger percentage of listeners to the average genre profile (which is the category profile). Therefore, rather than focusing on only 1000 true fans, amassing a broad demographic and psychographic fan base is a sustainable route to growth.

1.8. Thesis Structure

This thesis begins by discussing DoP literature in Section 2, including its usefulness and contexts where the pattern has been observed. Evidence to suggest that the Law of DoP might not hold for music listening is also presented. Contexts where brands are found to have similar buyer profiles are also presented, in addition to known deviations from the pattern.

Relevant music preference literature as a potential foil to the application of the law of DoP and the pattern that brand user-profiles seldom differ to music listening are also reviewed. Further disagreement regarding the effect of age on the development of music preferences is presented.

Sections 3 and 4 present Study One data, method of analysis and results, which examines the generalisability of the law of DoP for music listening.

Sections 5 and 6 is comprised of the data, method of analysis and results for Study Two, which is an investigation into the demographic, psychographic and media usage profiles of genre listeners.

Sections 7 and 8 present the data, research design, analysis and results for Study Three, which examines whether preferences for popular music peaks during a period of late adolescence or early adulthood.

Section 9 concludes this thesis with a discussion of results, contributions to theory and practice, limitations and future research.

2. Literature Review

2.1. Brands Compete in Line with the law of Duplication of Purchase

The law Duplication of Purchase (DoP) is an empirical generalisation in marketing which describes how brands share their customers with competitors. The Law states that the level of sharing between two brands is directly proportional to their penetration (number of buyers) (Goodhardt & Ehrenberg 1969). A brand therefore shares many of their customers with larger brands and far fewer with smaller brands.

The law of DoP is represented by the equation (Ehrenberg 1988; Goodhardt & Ehrenberg 1969):

$$b_{x/y} = Db_x$$

*$b_{x/y}$ *is the proportion of the sample who buy both brands x and y*

*b_x *is the proportion of the sample who buy brand x at least once in a given time period*

**D* *is the duplication coefficient which is the average observed duplications between each pair of brands divided by the overall average penetration*

This section provides a narrative literature review of the seminal DoP literature (Paré et al. 2015). Specifically, it provides a review of the readily available DoP literature and presents the contexts that the Law has been found to hold. Once the seminal DoP literature was sourced, the "cited by" function in Google Scholar was used to locate additional studies to demonstrate the generalisability of the Law. Each section is grouped thematically by the Law's known conditions and context (e.g. media, high-involvement).

2.1.1. Duplication of Viewing in media

DoP originated from early media audience research (e.g. Agostini 1961; Chatfield & Goodhardt 1975; Goodhardt 1966; Goodhardt & Ehrenberg 1969). By observing viewers who watched any pair of television programs (the duplicated audience), researchers observed a recurring pattern, the law of duplication of viewing (DoV). DoV states that the number of viewers that watch any pair of programs can be predicted by the audience size (or rating) of the latter program (Goodhardt & Ehrenberg 1969). Regardless of other factors such as program content or genre, the rating of the second program dictates the percentage of the duplicated audience (Goodhardt & Ehrenberg 1969). In addition to television programs, DoV occurs for television channels (Collins et al. 2003) and radio listening in New Zealand, where it is known as Duplication of Listening (DoL) (Lees & Wright 2013).

2.1.2. DoP in gaming and tourism

DoP also generalises to entertainment product categories. The Law holds for gambling purchases in the United States, Australia and Macao (Lam 2012; Lam &

Ozorio 2013). The generalisability of the observation was strengthened by the fact that the Macao study (Lam & Ozorio 2013) was conducted 10 years after that of the United States and Australia. DoP has also been successfully applied to tourist destinations (Mansfield & Romaniuk 2003). Using countries as brands, researchers observed that tourist destinations consistently followed the general DoP pattern across multiple sets of data and time periods. The finding was consistent upon replication and extension (Mansfield et al. 2003).

2.1.3. DoP in high involvement purchase contexts

The Law further generalises to high involvement purchases such as aviation fuel contracts and cars (Bennett 2004; Bennett & Graham 2010; Colombo et al. 2000; Ehrenberg 1975; Uncles & Ehrenberg 1990b). For television sets in China, brand switching is in line with penetration, such that consumers who purchase a second television brand are more likely to purchase one with high penetration (that is, a big brand) Bennett (2004). For European aviation fuel contracts, the proportion of airlines who have contracts with one fuel supplier and also have a contract with a second supplier, is dictated by the size of the second supplier's penetration – larger oil suppliers gain more customers from smaller oil suppliers and vice versa (Ehrenberg 1975). The finding is consistent upon replication (Uncles & Ehrenberg 1990b). DoP is also observed for automobile purchasing in France, the United Kingdom (Colombo et al. 2000), and Thailand (Bennett & Graham 2010).

2.1.4. DoP in high frequency purchases

DoP applies across a wide range of countries and product categories that are purchased on a regular basis. The pattern holds for numerous grocery product categories in the United Kingdom (Ehrenberg & Goodhardt 1970), soft drinks in the United States (Bass 1974) and instant coffee purchases in Japan (Keng et al. 1998). The Law holds beyond consumer packaged goods. Bennett and Ehrenberg (2001) observes DoP for Quick Service Outlets (QSOs) in South Australia and Dawes (2008) for Australian beer purchasing. Research demonstrates the generalisability of the Law of DoP for wine across brand, variety and region of origin in France (Cohen & Tataru 2011) and wine brand purchasing across price tiers in Australia (Romaniuk & Dawes 2005).

Table 1: Summary of literature where the Law of DoP has been found to hold

Author/Year	Consumption Context	Country/Region	Notable Deviations
(Agostini 1961) (Agostini 1962)	Magazines	USA & France	
(Goodhardt 1966) (Ehrenberg 1966) (Goodhardt & Ehrenberg 1969) (Ehrenberg & Goodhardt 1969) (Goodhardt et al. 1975) (Barwise & Ehrenberg 1988) (Collins et al. 2003)	Television program and channel viewing	UK and USA	Higher sharing for daytime programs on weekdays, pairs of programs on the same channel on different days and pairs of programs on the same channel on the same day

(Lees & Wright 2013)	Radio stations	New Zealand	Talk and music radio stations format partitioning
(Mansfield et al. 2003) (Dawes et al. 2009)	Tourist destinations	USA, Europe and Asia	Location-based partitioning
(Lam 2012) (Lam & Ozorio 2013) (Hand & Singh 2014)	Gambling	UK, USA, Australia, Macao	Grouping between horse racing and dog racing, which overshares buyers and under shares with scratch cards, lottery tickets and bingo. Higher social class is associated with higher duplication between racing gambling
(Ehrenberg 1975) (Uncles & Ehrenberg 1990b)	Aviation Fuel Contracts	Europe	
(Colombo et al. 2000) (Bennett & Graham 2010)	Automobiles	France, UK and Thailand	Clusters of French, German, Japanese and General Motor-made cars Luxury vs non-luxury car submarket
(Bennett 2004)	Television Sets	China	Higher sharing within the cluster of global television brands
(Ehrenberg & Goodhardt 1970) (Ehrenberg 1988) (Keng & Ehrenberg 1984) (Uncles & Ehrenberg 1990a) (Keng et al. 1998) (Anesbury et al. 2018b)	Consumer packaged goods	UK, USA, Australia	Price related submarkets
(Bennett & Ehrenberg 2001) (Bennett & Ehrenberg 2002)	Quick Service Outlets/Fast food services	USA and Australia	
(Dawes 2008)	Beer	Australia	Partitioning between beer brands part of the Fosters group
(Cohen & Tataru 2011) (Romaniuk & Dawes 2005)	Bottled wine and wine retail stores	France and Australia	Partitioning by wine variety and adjacent wine price tiers
(Uncles & Kwok 2009)	Retail stores	China	

2.2. The usefulness of the law of Duplication of Purchase

The law of DoP provides brands with an understanding of how they compete by showing who sales are likely to be lost to or gained from as a brand declines or grows (Dawes et al. 2009). The outcome of the Law is that there is a lack of segmentation in any market, and that all brands compete for customers most intensely with big brands (Ehrenberg 1988; Ehrenberg et al. 2004). Importantly, the Law enables a brand to benchmark the extent to which they are expected to share their customers with competitors (Ehrenberg et al. 2004). This allows a brand to focus their strategic attention on the major competitors (the big brands) and avoid focusing on a narrowly defined competitor set.

2.2.1. What are deviations from the law of DoP?

Deviations from the Law occur when brands share more or fewer customers than expected for their size. Such exceptions, although rare (Scriven et al. 2017), indicate submarkets or market partitioning (Sharp & Sharp 1997). Partitioning is often the result of functional differences (Lees & Wright 2013). For example, markets may be partitioned into a grouping of brands that share more customers with each other but share fewer customers with brands outside of the partition e.g. the instant coffee market is partitioned into caffeinated vs decaffeinated brands (Kalwani & Morrison 1977). Identification of partitions is useful as it provides an understanding of a market's structure by showing which brands are regarded as functionally similar and substitutable (Romaniuk & Dawes 2005). A strong case of partitioning is observed between leaded and unleaded petrol, such that petrol buyers typically bought leaded or unleaded but rarely both (Bennett et al. 2000; Scriven & Ehrenberg 1994). Similarly, in the automobile market, luxury cars are partitioned, with consumers typically buying luxury or non-luxury (Ehrenberg & Bound 2000). Clusters of French, Japanese, German, sporty and General Motors' cars are also found, indicating heightened competition within each grouping, and thus separate competition in a market partition (Colombo et al. 2000). Partitioning is also observed between filtered and non-filtered, and menthol and non-menthol cigarettes (Carter & Silverman 2004), geographically close tourist destinations (Mansfield et al. 2003) and Chinese and global television brands (Bennett 2008). Evidence of partitioning between talk and music radio stations (Lees & Wright 2013) is most similar to the context of this thesis. Although partitioning does occur, the effect is secondary to brand size as the overall DoP pattern of brands sharing customers in line with penetration still holds (Ehrenberg & Bound 1999). Dawes et al. (2009) notes that small deviations from the DoP pattern (≤5 percent) are likely a result of random sampling variation.

2.3. The law of DoP is part of the Dirichlet model

The law of Duplication of Purchase is described by the Dirichlet Model, which explains how frequently purchased consumer goods are bought when the market is stationary and unsegmented (Bass et al. 1976; Chatfield & Goodhardt 1975; Goodhardt et al. 1984). Specifically, it describes that each consumer has a certain purchase propensity to buy a given brand, which differs across heterogeneous consumers but remains steady at the aggregate level (Ehrenberg et al. 2004). This means that experienced consumers have steady purchase propensities and divided loyalty for when purchases are made and which brands they choose (Ehrenberg & Uncles 1999). However, sales of each brand show little variation in how frequently they are bought and there are no special groupings between various brands (Goodhardt et al. 1984). This reflects that while individuals are different, there is stability at the aggregate level. Consequently, the model describes and predict various brand purchasing patterns requiring only the brand and overall category penetrations and the purchase frequencies (Goodhardt et al. 1984). To date, the Dirichlet has been tested across a number of different markets and conditions including store choice (Keng & Ehrenberg 1984; Keng et al. 1998), packaged goods (Uncles et al. 1994), durables and services (Colombo et al. 2000; Ehrenberg 1988; Ehrenberg & Bound 2000; Ehrenberg et al. 2004; Sharp 2010), pharmaceutical prescriptions (Stern 1994; Stern & Ehrenberg

1995), industrial purchases (Pickford & Goodhardt 2000; Uncles & Ehrenberg 1990b), gasoline (Scriven & Ehrenberg 1994), television viewing (Barwise & Ehrenberg 1988), fruits and vegetables (Anesbury et al. 2018a) and online supermarkets (Trinh et al. 2017). While the model only applies to steady-state and non-partitioned markets, it does not imply that all markets should be stationary and non-partitioned (Ehrenberg et al. 2004).

The following five assumptions underpin the model (Bass et al. 1976; Chatfield & Goodhardt 1975; Ehrenberg et al. 2004; Goodhardt et al. 1984).

I. Each consumer buys from the category with a steady long-term probability, but is also prone to change in the short-term due to a number of factors. As a result of this variation among individual consumers, purchases are assumed to follow a "smooth" gamma type distribution. The Gamma has many non-and-light buyers and few heavy buyers.
II. Individual consumers' category purchases are assumed to be spread stochastically over time around each consumers' long run probability. Purchases follow a "zero-order" process meaning that the next purchase is independent of the previous purchase and as-if-random.

    Together, the Gamma (I) and Poisson (II) distributions form the Negative Binomial Distribution (NBD), where the distribution of purchases describes individual brand or the category buying as a whole. The Multivariate Beta (III) and Multinomial distribution (IV) assumptions relate specifically to brand choice.

III. Individual differences in consumers' brand choice probabilities follow a smooth Beta distribution, with a multivariate Dirichlet nature.
IV. Brand choice for any one purchase occasion occurs as if random, following a zero-order process. This means that brand choice is not dependent on the previous purchases, rather based on the zero-order probability. Therefore, a consumer will buy a brand as-if-random within their personal choice probabilities.
V. Brand choice probabilities are stable and independent from a consumer's frequency of purchase. Therefore, market shares remain similar for light, medium and heavy buyers.

2.4. What is the "brand" in music listening

An important point for consideration is whether a music genre, album, artist or song can be regarded as a brand in music, such that the law of DoP should be expected to apply at all four levels. For instance, while a genre could be considered a brand, it may also act as a category in different music competes for listeners within. However, the law of DoP has been found to hold for competition at levels that may be considered similar to a music genre. For example, in television viewing studies, the law of DoP was found to hold between television channels in addition to the individual programs aired within the same channel (Goodhardt & Ehrenberg 1969; Goodhardt et al. 1975). Further research in wine, demonstrates the application of the law of DoP for across

price tiers, variety and region of origin (Cohen & Tataru 2011; Romaniuk & Dawes 2005). This research shows the law of DoP holds across not only brand competition but a number of choice factors. By investigating DoP across all four levels of music listening (genre, artist, album and song), a holistic understanding of the structure of music listening can be obtained. This approach is made clear in Lees and Wright's (2013) radio listening study, which finds a partition between talk and music station formats, where DoP broadly holds between stations but more clearly applies within each of these two formats.

2.5. Why the law of DoP might not apply to online music listening

The previous sections provided an overview of DoP studies to demonstrate the Law's generalisability. However, there are unique characteristics of music listening that may impede the Law's generalisability, by violating some key assumptions of the Dirichlet model. This section discusses these aspects and presents a case as to why the law of DoP may not apply to music listening. Namely, these reasons relate to features of music streaming services such as music recommendation and potential clustering or partitioning of certain music styles.

2.5.1. Music choice may not follow a zero-order process

With many people consuming music online, especially through streaming services (International Federation of the Phonographic Industry 2018), music recommendation systems present the first challenge for the application of the law of DoP. Recommender systems aim to combat the overwhelming choice between millions of songs by suggesting music that an individual is predicted to like and subsequently listen to (Domingues et al. 2013). One method of recommendation is through a process known as collaborative filtering. This approach collects feedback about what music users like and groups them based on the similarity of their tastes to recommend music (Yapriady & Uitdenbogerd 2005). Another technique is content-based filtering, which makes recommendations based on music that is stylistically similar to previously liked music (Ricci et al. 2015). Other approaches such as demographic profiling, knowledge-based, constraint-based, community-based and hybrid systems are other types recommender systems (Ricci et al. 2015). Regardless of the method used, the premise of recommendation may disrupt the as-if-random, zero order process of music choice.

2.5.2. Music listening is context dependent

Studies suggest that an individual's music preferences are constantly evolving and largely dependent on environmental factors such as who an individual is with, their current mood or the time of day (Baur et al. 2012; Sahoo et al. 2012). Music also fulfils a range of functions such as relieving stress or boredom, filling empty background noise or acting as a vehicle for self-expression (Lonsdale & North 2011; North et al. 2000; Rentfrow & Gosling 2006). Consequently, the highly variable nature of music listening makes it difficult to understand patterns of consumption, and presents a

significant challenge in applying the law of DoP. For example, if an individual is listening to music to fill empty background noise, they may be less selective than if they were listening to music with a friend. Therefore, the repertoire of music consumed may vary significantly depending on the function and environmental factors.

2.5.3. Music might be partitioned

A logical assumption is that an individual may be more (or only) likely to listen to music that is stylistically similar, driven by distinct preferences. For example, listening to Blues music may increase the likelihood of listening to Jazz. Some researchers have used factor analysis to load music genres onto unified dimensions of style. For example, George and colleagues (2007) load Grunge, Heavy Metal, Punk, Alternative and Classic Rock onto a "rebellious" dimension (factor loadings: .73 to .84). Similarly, Rentfrow and Gosling (2003) load Blues, Jazz, Classical and Folk onto a "reflective and complex" dimension (factor loadings: .64 to .85). Such loadings may indicate clusters of functionally similar genres, which might result in an individual being more likely to listen to music that belongs to the same dimension and even avoiding other music. Market partitioning and segmentation may therefore occur. The likelihood of this occurrence is not unreasonable, given that the freedom of choice associated with online music streaming compared to traditional music consumption media e.g. radio. If an individual does not like particular music, they can choose not to listen to music it.

2.6. Applying the law of DoP to a New Category

The previous sections provided an overview of the generalisability of the law of DoP, demonstrating that it applies to consumer-packaged goods, media channels, entertainment and high involvement purchasing contexts. While deviations from the law of DoP are not uncommon, their effect is secondary as the overall pattern of the Law continues to hold. To date, the Law has not been applied to an online music listening context. While the Law describes brand competition for radio stations (Lees & Wright 2013) and television viewing (Goodhardt & Ehrenberg 1969), which are both similar to music listening, it cannot be automatically assumed to apply to music listening.

This thesis aims to determine if the law of DoP describes how people listen to music. In doing so, it seeks to extend the generalisability of the Law, or otherwise, strengthening it by discovering a boundary condition (Barwise 1995; Bass 1995).

2.7. Research Questions: Study One

Study One addresses two research questions:

RQ1a: Does music listening follow the law of Duplication of Purchase for (a) genre, (b) album, (c) artist, and (d) songs?

RQ1b: Is there evidence of any partitioning between genres?

2.8. Competing brands do not attract a special segmented buyer

Segmentation, the process of dividing the market into groups by demographics, psychographics, and behavioural variables, and targeting them with products and advertising, has long been claimed as the key to marketing success, because brands are thought to appeal to distinct types of customers (Kotler 1991; Lilien et al. 1992; Smith 1956). Yet, research demonstrates that brands sell to very similar customers in terms of demographic, psychographic and behavioural variables (e.g. Ehrenberg & Kennedy 2000; Hammond et al. 1996). This is a key empirical generalisation in marketing, which states that the customers of directly competing brands (otherwise known as a brand user-profile) seldom differs (Uncles et al. 2012) and seldom changes (Anesbury et al. 2017). Implications are that rival brands compete in one unsegmented mass market and that a buyer is a buyer, whomever they may be (Ehrenberg & Kennedy 2000; Kennedy & Ehrenberg 2001a; Uncles et al. 2012). While targeting a particular group of consumers may be successful among a small portion of the market, it risks excluding the many consumers that could be potential buyers. Therefore, understanding the customer bases of competing brands offers a complementary understanding to the law of Duplication of Purchase, which focuses on market structure and how brands compete.

2.9. The generalisability of brand user-profile research

The following sections present consumption contexts where the user-profiles of competing brands are found to be similar. In addition, where differences are found to occur are discussed, as well as why the large similarity in brand user-profiles is so generalisable. Finally, it concludes by presenting opposing evidence as to why music may attract different listeners.

2.9.1. Consumer packaged goods and services

Hammond and colleagues' (1996) seminal research assessed the degree that competing brands are actually bought by a special segmented customer. The original analysis approach compared the profile of the buyers of each brand (referred to as a user-profile) to the average profile of the category (reflecting what the average brand's buyer composition should look like). The context of this research was brand buying for 5,000 consumers in 23 consumer packaged goods (CPGs) categories and four markets (United Kingdom, United States, Germany and Japan). Remarkably, only one out of 200 brand user-profiles notably appealed to a distinct demographic group (deviation ≥ 5 percentage points (hereafter pp) from the average). Replication and extension analysed 25,000 consumers in 42 industries (i.e. CPGs, durables and financial and leisure services) and confirmed the generalisability of this finding to also include psychographic and media usage variables (Kennedy et al. 2000). To date, the user-profiles of competing brands are found to be highly similar for music outlets, high-street and supermarket retailers (Kennedy & Ehrenberg 2001a), Australian and New Zealand banking products (Lees et al. 2016), fruits and vegetables in the United States and India (Anesbury et al. 2018a) and emerging markets (Tanusondjaja et al. 2015).

Longitudinal research demonstrates that brand user-profile seldom differ and seldom change (Anesbury et al. 2017; Uncles et al. 2012). Mean Absolute Deviations (MADs) between the observed and average brand profile are low and typically around 3 pp (e.g. Hammond et al. 1996; Kennedy & Ehrenberg 2001a). While this finding generalises across multiple countries and categories of consumption, their context is dissimilar to music listening consumption, in that music does not have to be purchased at each consumption occasion. Therefore, on the merit of these studies alone, the finding that brand user-profiles seldom differ cannot be automatically assumed to apply to music listening.

2.9.2. Fashion and clothing Brands

Additional research has examined the user-profiles of luxury and clothing brands (e.g. Bennett et al. 2016; Patrick et al. 2016). In the United States and China, luxury and fashion/accessory brands were found to be more similar than different in their demographic and motive buyer composition (Patrick et al. 2016). However, 11% of deviations in the USA and 13% in China were over 10 pp, which contrasts with earlier findings in CPGs (e.g. Hammond et al. 1996; Kennedy et al. 2000; Uncles et al. 2012). For example, Kennedy et al. (2000) find only 2% of deviations over 10 pp. Similar research has observed broad similarity in the user-profiles for high-street fashion retailers (Bennett et al. 2016) and sportswear brands in the UK (Dawes 2009). However, this research is limited to demographic variables and does not include other relevant segmentation criteria i.e. psychographic variables. Differences have also been observed in a fashion context. For example, some high-street fashion retailers attracted a higher proportion of young (<24 years old) buyers (Bennett et al. 2016), while some sportswear brands over or underperformed among certain social class groups (Dawes 2009). However, such differences were rarely found and the overall brand profiles were highly similar. These contexts are more relevant to music listening than CPGs, especially given that fashion and music are often considered part of individual self-expression (Breward 2003; North et al. 2000). However, music consumption is more prevalent and contains considerably fewer barriers to purchase than luxury and fashion clothing consumption.

2.9.3. Television channels and programs audience

Early television audience research in the US and UK examined demographic (e.g. age) and usage variables (light, medium, heavy viewers), in order to determine whether different people watch different program types (e.g. light entertainment, sport) (Barwise & Ehrenberg 1988). Program types differed little in their demographic and usage audience composition. Exceptions such as sports channels, which attract more men, were observed. Replication extends this finding to television channels (e.g. BBC1 vs ITV1), which also attracts similar audiences (Collins et al. 2003; Sharp et al. 2009). In this case, exceptions were attributed to submarkets and functional differences e.g. Spanish-language channels appeal more to Spanish-speaking viewers.

2.9.4. Radio and print media

Listener profiles of radio stations in Australia and New Zealand have also been examined (Nelson-Field et al. 2005; Nelson-Field & Riebe 2011; Winchester & Lees 2013). Generally, radio stations appeal to the same audience in terms of demographic and product usage variables. However, some differences are noted. For example, The Rock 95.4 station reaches more males (deviation of +22 pp). Despite this difference, more than a third of The Rock's audience is female, despite its claimed core target of males (Winchester & Lees 2013). This is consistent with earlier radio research which finds that 51% of a radio stations' audience falls outside of its stated demographic audience (Nelson-Field et al. 2005). Irish Newspapers and print magazines are also more similar than different in their demographic reader profiles (Nelson-Field & Riebe 2011; Winchester & Lees 2016). However, where research in CPGs and retailers find MADs of around 3 pp (e.g. Hammond et al. 1996; Kennedy & Ehrenberg 2001a), Winchester and Lees (2016) find MADs between 4 and 13 pp and Nelson-Field and Riebe (2011) find that 20% of deviations are notable. While these differences are larger than other consumption contexts, Nelson-Field and Riebe' research (2011) demonstrates that media owner's far overestimate their claimed target audience, as 80% of audience characteristics were not notably different from the category average.

2.9.4.1. Contribution and gaps in media audience research

The aforementioned studies in television, radio and print (e.g. Barwise & Ehrenberg 1988; Nelson-Field & Riebe 2011) offer a highly comparable benchmark for this thesis. These studies provide evidence that media channels' claims of delivering a specific segmented audience are often overstated (Nelson-Field et al. 2011; Winchester & Lees 2013). However, generalisability is limited to demographic and media/product usage variables. Given the larger deviations observed in radio and print media, the same might be expected for music listening.

Table 2: Summary of relevant brand user-profile studies

Author/Year	Context	Country/ Region	Variables	Magnitude of Deviations
(Hammond et al. 1996) (Kennedy & Ehrenberg 2001b) (Lees et al. 2016) (Kennedy et al. 2000) (Uncles et al. 2012)	Consumer packaged goods, durables, financial and leisure services, durables	UK, USA, Germany and Japan	Demographic, attitudinal, lifestyle, media usage, ownership of microwaves and freezers	≤10% of cases ≥10 pp deviations 2-3 pp average MAD
(Kennedy & Ehrenberg 2001a) (Lees & Winchester 2013)	Music outlets/retailers and supermarkets	UK and Australia	Demographic, media usage and attitudinal	2 pp average MAD 4% of cases ≥ 5 pp 1% of cases ≥10 pp
(Singh et al. 2008)	Product Variants	USA	Demographic, ownership of microwaves and freezers	2.5 pp average MAD
(Patrick et al. 2016) (Bennett et al. 2016) (Dawes 2009)	Luxury, fashion accessory and sportswear brands, high street fashion retailers	USA, UK and China	Demographic and sociodemographic	11% of cases ≥10 pp (USA) 13% of cases ≥ 10 pp (China) 1 to 10 pp MADs
(Nelson-Field & Riebe 2011) (Barwise & Ehrenberg 1988) (Collins et al. 2003)	Television programs and channels	UK, Australia, New Zealand and Ireland	Demographic and product usage	6 pp average MAD
(Nelson-Field & Riebe 2011) (Winchester & Lees 2013)	Print media	Australia and New Zealand	Demographic and product usage	4 to 13 pp MADs
(Nelson-Field et al. 2005) (Nelson-Field & Riebe 2011) (Winchester & Lees 2013)	Radio	New Zealand	Demographic	51% of radio networks' audience falls outside their core demographic Radio 7 pp average MAD Largest deviation was 21 pp 20% of audience variables notable deviations
(Anesbury et al. 2018a)	Fruits and vegetables	USA and India	Demographic	1-3 pp average MADs
(Anesbury et al. 2017)	Consumer packaged goods	UK	Demographic and attitudinal	2 pp average MAD

2.10. Deviations in brand user-profiles

While studies across many different product categories and countries demonstrate that brands do not appeal to a unique segmented customer (e.g. Hammond et al. 1996; Kennedy & Ehrenberg 2001a), some notable differences in brand user-profiles have been found. For example, some competing UK music retailers are shopped at by more females and others by more males (Kennedy & Ehrenberg 2001a). A higher proportion of households with children have been found to buy pre-sweetened breakfast cereal (Hammond et al. 1996). However, such differences are small and rarely justify a separate marketing strategy (Kennedy & Ehrenberg 2001a). Deviations typically indicate functionally different submarkets. For example, deeming or pension accounts are held by far more customers over 50 years old (Lees et al. 2016). However, these accounts are only available to retirees and therefore this skew is expected. Luxury brand Chloe unsurprisingly skews more to females as it does not produce menswear (Patrick et al. 2016). Naturally, a Scottish submarket for Scottish banks (i.e. Bank of Scotland, Royal Bank of Scotland and Clydesdale) occurs (Kennedy et al. 2000) and lower socio-economic consumers shop at budget supermarkets (Kennedy & Ehrenberg 2001a). The existence of such submarkets is typically already well-known and obvious (Kennedy et al. 2000).

2.11. Types of segmentation

While these studies show that brand user-profiles seldom differ at (1) brand level i.e. buyers of Coca-Cola are similar to buyers of Pepsi, it is important to acknowledge the existence of segmentation at (2) category and (3) stock keeping unit (SKU) level (Kennedy et al. 2000). Category or sub-category segmentation refers to functionally different and non-substitutable products. For example, buyers of cat food have cats and luxury car buyers tend to be greater in wealth (Uncles et al. 2012). This is referred to as "knowing your market" and is usually obvious (Kennedy & Ehrenberg 2001a). It is also recognised that different SKUs or product variants may have distinct followings. For example, larger families may buy larger pack sizes (Kennedy et al. 2000). These are important distinctions to consider in the context of this thesis, for example, in music, what is considered the "brand" between the genre, artist, album or individual song?

2.12. Brand user profiles seldom differ due to substitutability and repertoire buying

The observed lack of brand segmentation is predominantly caused by the fact that competitive products are substitutable (Kennedy & Ehrenberg 2001a). Many brands differ little in taste, technical formulation, performance, functional features and even sometimes appearance, resulting in a lack of difference between many brands (Kennedy et al. 2000; Kennedy & Ehrenberg 2001a; Uncles et al. 2012). A proposed reason for this similarity is that competitors copy each other in order to remain competitive (Kennedy et al. 2000). Any brand's competitive advantages are also copied over time, compounding this lack of brand difference (Kennedy & Ehrenberg 2001a; Uncles et al. 2012). Romaniuk et al. (2007) finds that, on average, across 17 markets, 90% of a brands' buyers do not see that brand as differentiated from competing brands.

Most consumers are aware of the fact that a brand is a commodity with a name, and thus any reputable brand is sufficient in the absence of any functional differences (Kennedy & Ehrenberg 2001a). Therefore, in low-involvement categories, consumers typically buy from a repertoire of brands, rather than solely buying one brand (Banelis et al. 2013; Goodhardt et al. 1984; Sharp et al. 2002). This type of multi-brand buying occurs in consumer packaged goods (Dawes 2008), store choice (Keng & Ehrenberg 1984), television channel choice (Barwise & Ehrenberg 1988) and industrial markets (Ehrenberg 1975). As a result, customers populate the user bases of many brands, which leads to the similarity in profiles (Uncles et al. 2012).

2.13. Why music listener profiles may differ

2.13.1. Competitor copying is discouraged in music

While brand substitutability and competitor copying typically compounds a lack of difference in the profiles of competing brands, the same is not entirely true for music. As a creative art, musicians are lauded for their creativity and originality. This notion is perfectly encapsulated by Deliège and Wiggins (2006, p. 161):

"To be a great artist... one must have unusual capacity for creativity, and so create products of the highest quality and upmost originality."

The importance of creativity to musical performance is agreed upon (Clarke 1995; Persson 2001). The encouragement of originality is demonstrated by the discouragement of competitor copying through recent legal proceedings e.g. where musicians or estates litigated against songs such as Robin Thicke's 'Blurred Lines', Led Zeppelin's 'Stairway to Heaven' and the Verve's 'Bittersweet Symphony'.

It is acknowledged that there are limits to originality and an inherent element of inspiration from other musical works. David Bowie himself said: "The only art I'll study is art I can steal from", while Jazz music, for instance, has certain chord progressions and notes that limit its potential originality (Mito 2015). Furthermore, Pop music is often mocked for its simplistic four chord structure (The Axis of Awesome 2011), which seems to reflect the genres' uniformity. Notwithstanding the potential limits to creativity and originality in music, its discouragement provides a consideration as to why brand user-profiles may differ, given that artists are encouraged to create unique music products.

2.13.2. Music may not be substitutable due to unique needs fulfilment

Another reason why user-profiles may be different in a music context is that one musical piece may not necessarily be substitutable for another. Music is reported to fulfil different needs such as filling background noise, encourage social interaction, the expression of image and mood management and regulation (Lonsdale & North 2011; North et al. 2000; Rentfrow & Gosling 2006; Tarrant et al. 2000). Therefore, different styles of music may cater towards the fulfilment of these differing needs, which is akin to functional differences between brands. A reasonable assumption is that a genre such

as Heavy Metal may fulfil very different needs to Classical music. However, this may balance out on the aggregate level, such that an individual consumes a range of different music styles to fulfil the range of needs experienced. Nonetheless, the proposed differing needs that music fulfils may not be evenly distributed through the population, which is why listener profiles may differ for music.

2.14. Conflicting evidence in the music literature

Findings in the music literature claim that music preferences or listening are segmented by demographic and/or psychographic variables (e.g. Rentfrow & Gosling 2003; Savage 2006). This is in opposition to the finding that brands attract a similar customer base and the law of DoP. Demographic and psychographic differences in music listening are now discussed. In this thesis the aggregate demographic and psychographic composition of the listeners a particular music genre is referred to as a listener profile.

2.14.1. Demographic differences in music preference

Differences in music preferences have been linked to a range of demographic and lifestyle variables, including (but not limited to) age, gender, ethnicity, social class factors, health, relationships, living arrangements, beliefs, crime, media usage and leisure time (Christenson & Peterson 1988; Holbrook & Schindler 1989; North & Hargreaves 2007a, 2007b, 2007c; Savage 2006). As an example, Rock was found to have a listener profile of young, male, ethnically white, middle-class and managerial workers or technicians (not professionals) (Savage 2006). Fans of R&B, Hip-Hop/Rap and DJ-based music are reported as being the least likely to drive, although this is acknowledged as being attributable to their lower age (North & Hargreaves 2007c). However, these studies are limited in generalisability due to some weaknesses. North and Hargreaves' research, (2007a, 2007b, 2007c) confines respondents to selecting only one from 35 music genres that they consider to best describe their current music taste. This is problematic as respondents may enjoy more than one genre, but are included only in one genre's listener profile. Savage's (2006) research uses survey data from the Cultural Capital and Social Exclusion (CCSE) project, which only includes eight genres and eight musical works. The small number of genres and musical works limit the generalisability of findings. The face-to-face data collection method may also create a social desirability bias (Nederhof 1985).

2.14.2. The effect of nostalgia on popular music preferences

Nostalgia, as an extension of age, has been considered a potential influence on popular musical preferences. Popular music preferences peak when an individual is around 24 years old, which reflects tastes acquired during a potential critical period in an individual's life (Holbrook & Schindler 1989). This critical period is referred to as late adolescence or early adulthood. The effect of nostalgia therefore appears to condition popular music preferences, such that an individual is more likely to prefer popular music released during their mid 20s. A replication conducted in Germany finds a dramatic shift in this age preference peak towards 8.6 years of age (Hemming 2013). Holbrook and Schindler (2013) investigated Hemming's data and argued that

their original claim is still valid, due to some weaknesses of the replication study (Hemming 2013). Firstly, several unreliable observations may have influenced the location of the age peak. Further, all subsamples less than n = 50 were arbitrarily removed leaving only 78 observations. Reanalysis of Hemming's data found an age peak at 19.2 years of age, which is considerably closer to the original finding of 23.5. Age may therefore influence popular music preferences. However, inconsistent findings and disagreement underlines the need for further investigation.

2.14.3. The role of psychographics and personality in music preference

Psychographic variables, particularly personality, have been related to music preferences. Rentfrow and Gosling's (2003) research is considered the landmark study in music preference and personality research (Dunn et al. 2012). The study contributed a four-factor model of music preferences which was related to personality. Fourteen genres were loaded onto one of the four music dimensions, which are: "Reflective and Complex" — Blues, Classical, Folk and Jazz, "Intense and Rebellious" — Alternative, Heavy Metal, Rock and Country, "Upbeat and Conventional" — Country, Pop, Religious, Soundtracks, and "Energetic and Rhythmic" — Dance/Electronica, Rap/Hip-Hop, Soul/Funk. As an example of the relationship between music preference and personality, "Reflective and Complex" genres (Blues, Jazz, Classical, Folk) were positively related to the openness[1] personality trait (Rentfrow & Gosling 2003). The relation of this four-factor model to the Big Five personality traits has been replicated (Delsing et al. 2008; Dunn et al. 2012; George et al. 2007; Zweigenhaft 2008). However, inconsistent results are found. For example, Rap and Dance are grouped in Dunn et al. (2012) research but not in Delsing's (2008) or George's (2007). Further, Dunn and colleagues (2012) note that correlations between personality and music preferences reported in theirs and others' studies are generally weak ($r < 0.30$) (e.g. George et al. 2007; Zweigenhaft 2008). Issues regarding generalisability also exist due to the common use of small undergraduate samples (e.g. Zweigenhaft's (2008) n = 83 undergraduate sample). Despite these inconsistencies and weaknesses, personality could still be an accurate predictor of music preference. Music listener profiles may therefore differ.

2.14.4. Personality vs demographics in music preference

The role of personality in music preference has been explored in further research, sometimes in conjunction with demographics (e.g. Greenberg et al. 2016; North 2010; Rawlings & Ciancarelli 1997). However, there is conflicting evidence as to whether demographic or psychographic variables are more accurate predictors of music preference. Greenberg (2016) compared the influence of a limited number of demographic variables (age, gender, education) and the Big Five personality traits in relation to music attribute preferences. Greenberg concluded that personality traits predict music preferences far beyond demographic variables. This contrasts with

[1] Openness to experience: an individual's propensity toward intellectual curiosity, imagination, aesthetic and emotional sensitivity, and originality (Costa & McCrae 2008)

North's (2010) study of 36,518 music listeners, where music preference was more closely related to demographic variables (gender, sex and particularly age) than personality. However, both personality and demographic variables explained only 2 to 5% of the variance in music preferences. Behavioural research similarly finds that demographics has a small effect on music listening, explaining only 4.9% of variance in music choice (Baur et al. 2012). However, this research did not examine personality's effect on music preference. These mixed findings merit more rigorous investigation.

2.14.5. Motivations for listening might cause segmentation in preferences

Researchers have also investigated motivations for listening to music. Such motivations are to provide background noise, encourage social interaction, express an image to others, self-actualization and fulfilment of emotional and social needs (Lonsdale & North 2011; North et al. 2000; Rentfrow & Gosling 2006; Tarrant et al. 2000). Studies focusing on more general media consumption consider hedonic and eudaimonic motivations (Vorderer 2011). Hedonic motivations are characterised as consuming media for pleasure or enjoyment (Vorderer et al. 2004), while eudaimonic motivations consider feelings of meaningfulness and contemplation (Oliver & Bartsch 2010; Oliver & Raney 2011). Eudaimonic motivations are considered a complementary perspective to hedonic motivations, as for example, reasons for consuming a film such as Hotel Rwanda may not be aptly explained by feelings of pleasure or enjoyment (Oliver & Raney 2011). Oliver and Raney's (2011) two-factor scale encapsulates both hedonic and eudaimonic dimensions. The relationship between these motivations and film genre preferences were also assessed. They find, for example, that eudaimonic motivations are associated with a greater preference for Nonfiction, Dramas and Science-Fiction films but less associated with a preference for Comedies and Action Adventure films (Oliver & Raney 2011). Hedonic and Eudaimonic motivations and their relationship to film genre preferences could present an additional cause for segmentation in music listening. This scale has not yet been applied to music genre preferences and will therefore form another segmentation variable to be tested in the brand user-profile analysis of this thesis.

2.15. Why re-examine music listener profiles?

Music preferences and the role of demographics and personality has been investigated widely (e.g. Dunn et al. 2012; North & Hargreaves 2007c). However, these studies are limited in generalisability for a number of reasons. For example, Zweigenhaft's (2008) sample consists of 83 former or current students from a university in North Carolina. The sample is overly representative of females and Caucasians (80% and 77% of the sample respectively). There is also disagreement regarding the predictive ability of demographic and psychographic variables. While some studies find personality is a superior predictor (Greenberg et al. 2016), others find that demographics are more predictive of listening behaviour (North 2010). A large emphasis is placed on correlations that reach statistical significance despite sometimes being weak, that is, $r \leq 0.33$ (Dunn et al. 2012). Low correlations, inconsistent and non-generalisable findings suggest that prior differences in music preference may be

overstated. An example of non-generalisable samples and low correlations used in studies is shown in Table 3.

Table 3: Example of studies where correlations between music preference and personality are low.

Author/Year	Sample/Data	Country/Region	Correlations Reported
(Rentfrow & Gosling 2003)	Study (S) 1,2,3: 74, 1704 and 1383 (respectively) self-selected University of Texas undergraduates S4: 10 users audopgalaxy.com music collections S5: sample of 140 songs S6: S2 and 3 samples	United States	**r ranges from .**01 to .44
(Delsing et al. 2008)	2334 adolescent children in grades 7-12, aged 12-19. 1097 boys (1234 girls) 75.2% Dutch, 2.4% Surinamese/Antillean, 9% Moroccan, 3.9% Turkish, 3.7% other ethnicity Subsample 1243 adolescents 1044 completed all four measurements	Netherlands	**r ≤** .33
(George et al. 2007)	358 participants aged 18-70 57% female, 71% Caucasian, 7% Asian, 12% African-American, 3% Hispanic, 7% other ethnicity 33% liberal arts university students	Canada	**r ≤** .43
(Zweigenhaft 2008)	83 current or former students from Guilford College in Greensboro, North Carolina 80% female,77% white, 16% ethnically coloured, 17% > 23 years old	United States	**r ≤ .4**4
(Dunn et al. 2012)	Study 1: N=395 self-selected participants, employees of Royal Phillips Electronics Study 2: N=138 (subsample of study 1) Mean age = 36.5 (study 1) & 36.4 (study 2) 85% male 51% Dutch, 13% American (US), 9% French, 5% German, 4% Belgian, 3% British, 8% other European countries, 1% Latin-American, <1% Canadian, 3% Asian	29 nationalities represented	**r ≤** .27
(Greenberg et al. 2016)	Study 1: 102 musical pieces selected from (Rentfrow 2012) Study 2: 9456 self-selected Facebook users aged 18 to 65 61% female	Not specified	**r ≤** .23
(Rentfrow & Gosling 2006)	Study 1: 60 self-selected University of Texas undergraduates, mean age = 18.4, 55% female Study 2: 74 self-selected University of Texas undergraduates, mean age, 40.5% female	United States	**r ≤** .47
(Rentfrow & Gosling 2007)	Study 1: 206 University of Texas undergraduates aged 17-27, 58.3% female, 19.4% Asian, 1% African American, 9.2% Hispanic, 60.2% White, 10.2% other ethnicity Study 2: 87 University of Texas undergraduates aged 17-40, 59.3% female, 23.2% Asian, 4.3% Hispanic, 72.5% White	United States	**r ≤** .33

2.15.1. Managerially significant results

A focus on p-values and statistical significance is criticised for perpetuating single study publications (Nelder 1999) and diverting the attention away from results that are actually important to marketing practice (Kennedy et al. 2014). Hammond et al. (1996) offers an alternative approach for investigating the demographic and psychographic profiles of brands. Unlike music studies, replication of Hammond et al.'s (1996) research finds consistent results (e.g. Kennedy & Ehrenberg 2001a; Kennedy & Ehrenberg 2001b; Uncles et al. 2012). Importantly, interpretation of findings is grounded in managerial significance rather than statistical significance. This diminishes the importance of p-values and elevates the role of clear and obvious differences in brand profiles. Thus, results are meaningful and useful to marketing practitioners.

Given the aforementioned weaknesses of studies in the music literature, the second research question addressed in Study Two of this thesis is:

RQ2a: Do music listener-profiles differ by demographic or usage variables?

RQ2b: Do music listener-profiles differ by psychographic variables?

Due to the large emphasis placed on age as a variable that influences music preference, and evidence which suggests it is single most distinguishing variable between listeners of different music (see Baur et al. 2012; North 2010), a third research question is also considered. Specifically, this question seeks to address the conflicting findings between Holbrook and Schindler (1989) and Hemming (2013) concerning the effect of age and nostalgia on the development of popular music preferences. These conflict merit further investigation. This third question may also be considered an extension of RQ2a, which examines the impact of demographic variables on music listening.

The question to be addressed in Study Three is:

RQ3: Do preferences for popular music peak during the period of late adolescence or early adulthood?

3. Study One Method

3.1. Overarching research methodology

The following sections will outline the overarching research methodology adopted in the thesis. Firstly, it begins with an explanation of Empirical Generalisations and how they can be established. Following, is the importance of replication research and specifically differentiated replication research designs in establishing and strengthening Empirical generalisations.

3.2. Understanding Empirical Generalisations

An empirical generalisation (EG) is "a relationship between two or more variables that has been observed across a range of conditions" (Uncles & Wright 2004, p.5). Empirical Generalisations are grounded in data and not necessarily explanatory theory. They may be later explained by a theory, becoming an "empirically grounded theory" (Ehrenberg 1995). For an observation to become an EG, the same lawlike pattern should recur over a range of conditions. There may also be certain conditions where an EG will fail to hold, which are known as boundary conditions (Bass 1995).

3.2.1. Characteristics of good Empirical Generalisations

According to Barwise (1995) and Uncles (2004), there are five characteristics of good EGs:

1) **Scope**. EGs must hold under a wide range of conditions. Conditions where an EG does not hold should also be predictable. These are referred to as boundary conditions.

2) **Precision.** An EG should describe a phenomenon in a manner that is reasonably exact without being too broad or narrowly focused.

3) **Parsimony.** EGs should be simply expressed regardless of the level of complexity involved in its formulation – "less is more".

4) **Usefulness.** Practitioners must find an EG useful and be able to apply it or at least assist them in thinking about practical issues.

5) **Link with Theory.** Once a phenomenon has been observed there is then something to explain. Why an EG occurs should therefore be explained, in some part, by theory.

3.2.2. Many sets of data are crucial in establishing EGs

To establish EGs, the focus is on identifying "significant sameness" across many sets of data (MSoD) (Barwise 1995; Lindsay & Ehrenberg 1993). While single sets of data may produce statistical correlations, they reveal little about the generalisability of results (Ehrenberg 1990). When equipped with MSoD, having established that the main effect still exists, the emphasis shifts towards testing whether the effect generalises across varied conditions such as time, context and country (Ehrenberg 1995). This

means that significant sameness, that is, whether the prior model holds again across the new data, takes precedence over statistical significance (Ehrenberg 1990). Therefore, finding the same results across multiple datasets is fundamental to establishing generalisable, lawlike patterns, and ultimately empirical generalisations (Ehrenberg 1990, 1995).

3.2.3. Replications establish Empirical Generalisations

A replication is a duplication or extension of a previously published empirical study, which tests whether the same results can be found upon repetition (Hubbard & Armstrong 1994). Finding the same result over multiple conditions is crucial in establishing EGs and principal to "good science" (Ehrenberg 1995; Madden et al. 1995). This provides confidence in previous findings and guards against falsehoods or incorrect results (Hubbard & Armstrong 1994; Uncles & Wright 2004). Replications are also a crucial component of meta-analyses (Eden 2002). A meta-analysis combines findings from multiple studies on the same topic to assess the generalisability of findings (Hubbard & Armstrong 1994). According to Allen and Preiss (1993), a meta-analysis, when informing a new study, not only unifies existing data and reduces sampling error, but offers provisions for future research. Consequently, replication and meta-analysis are complementary, for without replications, meta-analysis have nothing to synthesise. This research study replicates previous studies, contributing to the Duplication of Purchase, brand user-profiles and music literature.

3.2.4. Differentiated replication design

Replications may be either close or differentiated in design. Close replications duplicate the research design of the original study as closely as possible, testing whether the original researchers' findings are valid (Hubbard & Armstrong 1994; Lindsay & Ehrenberg 1993). Differentiated replications vary the conditions, such as the time or place, to establish the range of conditions in which the original findings continue to hold (Lindsay & Ehrenberg 1993). Differentiated replications are therefore useful in extending the conditions that an EG holds, as well as uncovering any boundary conditions, which are contexts where an EG fails to hold. This involves the careful consideration of the new condition to be varied, then observing whether the EG continues to hold or fails to hold (Uncles & Wright 2004). This thesis aims to examine a new condition in online music listening employing a differentiated replication design and a many sets of data approach.

3.3. Study One: a differentiated replication of the law of Duplication of Purchase

Chapter Three begins by outlining the many sets of data approach and a description of the data used in this research. In this section, the method of analysis for determining the fit of the law of Duplication of Purchase to music listening is explained.

3.3.1. The acquisition of data

Consistent with a MSoD approach (Barwise 1995; Lindsay & Ehrenberg 1993), four individual datasets collected between 2013 and 2014 serve as primary data. The datasets were obtained from Last.fm using their publicly accessible Application Programming Interface (API). Last.fm is an online personalised radio station and music recommender that also collects individual level music listening data (explained in further detail in 3.3.2). Users of Last.fm agree to having their listening behaviour tracked in order to receive recommendations, to share music, and for their own interest in their listening behaviour. Specifically, the datasets are the four largest "interest" groups on the platform during 2013-2014. These interest groups are genre-based and are specifically centred around self-identified fans of (1) Indie & Alternative, (2) Heavy Metal, (3) Classical, and (4) Trance, which form the names of each dataset used in this thesis. The Heavy Metal, Classical and Trance datasets were merged to create a fifth dataset, (which will be referred to as the "Last.fm" dataset). This was actioned due to the larger size of the Indie & Alternative dataset, which contains around 15,000 listeners. Merging the three smaller datasets creates a listener base of 11,000, which more similarly resembles Indie & Alternative's size. All datasets were not merged as the larger Indie & Alternative dataset would dominate the analysis of the three smaller merged datasets. This would render the merged dataset as a duplicated analysis of the Indie & Alternative dataset. This is because the listening behaviour of users in the Indie & Alternative dataset would be more likely to reach the brand selection criteria for analysis (see section 3.4.2 for more on brand selection criteria). One option that could have been considered is to select a random subset of users from the Indie & Alternative dataset to more closely resemble the smaller dataset's sample sizes and then merging the four datasets. However, this was not pursued in this analysis as the research team was satisfied with the number of datasets.

In total, the data consists of music listening behaviour from around 27,000 unique users for a year of music listening. This forms the primary behavioural data to be analysed in this thesis. Of note is that these datasets are not limited to songs from only these genres. For example, the Classical data contains logs of genres other than Classical, as they are comprehensive records of an individuals' listening behaviour.

Table 4: Sample representativeness in comparison to US census data. Source: (U.S. Census Bureau 2018; U.S. Census Bureau Population Division 2017, 2019)

	Sample (%)	US Census (%)		Sample (%)	US Census (%)
Age			**Gender**		
18-24	13	9	Male	47	49
25-39	26	21	Female	53	51
40-54	26	19			
55+	38	29	**Race**		
			Caucasian or white	80	77
Region			African American or Black	11	13
Northeast	18	17	American Indian or Alaskan Native	2	1
Midwest	21	21	Asian	4	6
South	38	38	Hispanic/Latino/Spanish	6	18
West	23	24	Native Hawaiian or Pacific Islander	<1	<1

The collected survey data closely resembles US census data.

Supplementary data is from a nationally representative survey in the United States collected in 2019 (n = 1,036). A comparison of the sample's representativeness and U.S. Census Bureau data is shown in Table 4. The data was primarily collected for Study 2 and measures claimed past weekly music listening. It serves as a secondary dataset for Study One. From this point in the thesis, the use of "brand" is used to mean genre, artist, album or song, depending on the context of discussion.

3.3.2. How Last.fm logs data

Last.fm uses a feature called "scrobbling", which records music listening behaviour and uses this information to make personalised recommendations. The scrobbling feature supports a number of streaming services such as YouTube, Spotify, Apple Music, Google Play Music and Pandora (for a full list see (Last.fm Ltd 2019). Listening is only recorded for songs that are longer than 30-seconds and played for at least half of its duration, or a minimum of 4 minutes (Last.fm 2013).

3.3.3. Preparing Last.fm data

As illustrated in Table 5, the data consists of four large datasets, ranging from 7 million (Trance) to 48 million (Indie & Alternative) records of listening behaviour (or 'logs'), totalling 84 million rows of data. Because Last.fm logs music listening from multiple platforms including Spotify, Apple Music and YouTube, the data presented significant challenges in the consistency of the variables. For example, in the song field, there might be different capitalisation (which affects counts) or missing entries in the artist field. While each dataset contains tens of thousands of genres, hundreds of thousands of artists and albums and millions of songs, not all are included the analysis. This is to avoid sampling error such that some brands may not contain a sufficient number of listeners, in addition to tractability in analysis and presentation of results. Further, these genres are later categorised using Rentfrow and Gosling's (2003) Short Test of Music Preference genre categorisation (STOMP). This is further discussed in section 3.4.4.

The following steps were therefore undertaken to clean the data:

- Aggregation of song, artist, album and genre tags, with different capitalisation or spelling to all lower case; and,
- Removal of non-alphanumeric characters such as bar slashes, full stops and commas.

Table 5: Last.fm data statistics illustrating the size of the datasets (time period = 486/487 days)

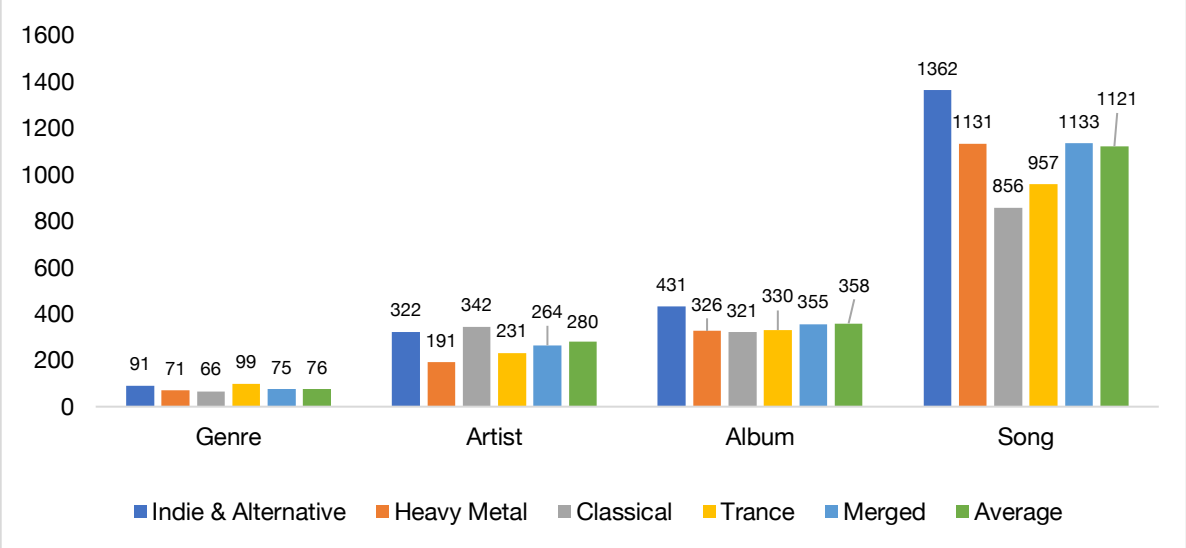
Self-Identified Interest Group	Genres	Artists	Albums (thousands)	Songs	Number of Unique Users	Number of Listens / rows of data (millions)
Indie & Alternative	21	356	678	2,048	15	48
Heavy Metal	15	184	390	1,218	5	17
Classical	19	270	504	1,709	3	13
Trance	12	211	318	906	3	7
Last.fm (Heavy Metal, Classical and Trance)	23	473	1,790	3,645	11	37

All datasets contain a large number of brands. There are the most brands at song level.

3.3.4. Repertoire Size Statistics

Figure 1 shows the average number of unique genres, artists, albums and songs, listened to in a year. This is known as repertoire size, which is a metric indicating the number of brands that a user purchases/listen to. One clear pattern that emerges is that repertoire size increases from genre to song level. Users listen to approximately an average of 80 genres, 270 artists, 350 albums and 1100 songs in a year. This is logical given that there are many more songs than genres (see Table 5). Repertoire size appears to be a consequence of number of brands. That is, one genre, artist or album may encompass many songs, which is the broadest level of listening. Importantly, these statistics show that most music listeners do not limit themselves to a small selection of genres, artists, albums or songs and in fact consume a range of different music. Given the high prevalence of multi-brand music listening, DoP analysis is appropriate to apply to these datasets. The DoP analysis procedure will be discussed in the following sections.

Figure 1: Average number of unique 'brands' listened to in a year (repertoire size)



Many more songs are listened to than genres.

3.4. Duplication of Purchase analysis

The law of Duplication of Purchase (DoP) is an empirical generalisation which describes how brands share their customers. Specifically, the Law states that the level of customer sharing of brand X's customers with brand Y is dictated by the penetration of brand Y (Goodhardt & Ehrenberg 1969). A brand is therefore expected to have many of its customers also purchasing (or in this case listening) from larger brands and far fewer of its customers purchasing from smaller brands (Sharp & Wright 1999). The Law provides insight into the structure of a market by revealing how brands share customers and importantly how this sharing may deviate from expectations (Ehrenberg et al. 2004). This enables brands to identify their main competitors and which other brands they are likely to gain or lose its sales to and from (Dawes et al. 2009; Ehrenberg et al. 2004).

3.4.1. Producing DoP tables for analysis

To identify whether the law of DoP describes music listening, the level of listener overlap (also known as duplication) between each pair of brands is calculated. For example, what proportion of Rock listeners, also listen to Pop, Country, Hip-Hop/Rap and so on. This calculation is obtained through the use of a Python script in RStudio version 1.1.463 for the Last.fm data and SPSS Statistics version 24 for the survey data. Once raw counts are generated they are converted into a percentage of that brand's listening base. For example, 297 of the 538 people who listened to Rock also listened to Pop, which is 55% of Rock's listening base. Once this process is repeated for every brand, they are ordered from largest to the smallest by the size of their listening base. Next, crosstabulation counts for each brand sharing listeners with itself are removed as it is naturally 100%. For example, the proportion of Rock listeners who also listen to Rock is blanked. Column averages are calculated, which indicates, on average, the proportion of listeners that also listened to a second brand. The data is now in the form as shown in Table 6 and ready for analysis.

Table 6: Example of a DoP table showing the expected pattern of sharing.

Genre	Penetration (%)	% who also listened to:					
		Rock	Pop	Country	Hip-Hop/Rap	R&B/Soul/Funk	Classical
Rock	52		55	42	32	28	23
Pop	46	62		43	42	35	23
Country	39	55	50		33	26	22
Hip-Hop/Rap	31	53	63	41		55	22
R&B/Soul/Funk	28	52	57	37	61		20
Classical	22	54	49	39	31	25	
Average Duplication		62	55	42	37	31	23

**note: this is not a table of results

In a DoP table, the overall pattern seen is that the level of brand sharing declines from left to right as brand size (penetration) decreases down the column (Dawes et al. 2009). Table 6 reads as 55% of Country listeners also listen to Rock, 50% of Country listeners also listen to Pop and so on. The general DoP pattern is observable in the average duplication row, which decreases from left to right in line with brand penetration.

3.4.2. Brand selection criteria

Due to the large number of brands at genre, artist, album and song level, many brands have small listening bases. Such small sample sizes can distort sharing levels. For example, if the genre "ethereal" has only one listener, it can only share a maximum of one listener with any other genre, which is 100 percent of its listening base. For this reason, and for ease of analysis, DoP analysis for the Last.fm datasets are therefore limited to the largest 99 brands in penetration, and an aggregated "all other" brand encompassing any brand not in the largest 99.

3.4.3. Tests of fit: Is listener sharing driven by brand size?

To test whether the observed data follows a DoP pattern where brands share their customers in line with penetration, average duplication values are correlated with brand penetrations using Pearson's correlation coefficient. Correlations range from -1 to +1, and coefficients closer to 1 indicate a highly significant positive relationship (Field 2009). Next, the duplication coefficient (D) is calculated by dividing the average observed duplications by the average penetration of all brands. The D coefficient can be interpreted as the level of competitive intensity between brands (Dawes & Nenycz-Thiel 2013). For example, a D coefficient of 2 means that the proportion of Brand 1's listeners that also listen to Brand 2 will be two times the penetration of Brand 2. Next, the D coefficient is multiplied by each brand's observed penetration in order to provide the theoretical or expected average duplication. Differences between the observed and theoretical duplication values are calculated and reported as mean absolute deviations (MADs) and mean absolute percentage errors (MAPEs). MADs and MAPEs are commonly used measures of fit (Armstrong & Collopy 1992; Armstrong 2001). As "all other" is an aggregation of a number of different brands, and therefore not an actual brand, it is not included in tests of fit measures.

There is no consistent deviation threshold used in DoP studies. Some studies adopt a 10-pp threshold (e.g. Cohen et al. 2012) while others assess the general fit between the theoretical and observed DoP values (e.g. Dawes 2008). As noted by Driesener and colleagues (2017), the marketing literature provides little guidance regarding an acceptable benchmark for assessing MADs and MAPEs, other than that they should be low. Therefore, the general pattern of MADs and MAPEs are assessed rather than any one specific benchmark.

Across the thesis, data is presented in line with the principles of data reduction (Ehrenberg 1982). MAD and MAPE results are reported as one significant figure with no decimal places. However, R values are reported as two significant figures. This is because the difference between reporting R values as 0.9 (if reported as one significant figure) rather than 0.97 (two significant figures), is much more meaningful than the difference between a MAD of 4.2 and 4.0.

3.4.4. Testing if brands are partitioned from the rest of the market

Deviations from the law of DoP occur when brands share more or fewer customers than expected. The level that brands are expected to share customers can be estimated by the formula (Ehrenberg 1988; Goodhardt & Ehrenberg 1969):

$$b_{x/y} = Db_x$$

*$b_{x/y}$ *is the proportion of the sample who buy both brands x and y*

*b_x *is the proportion of the sample who buy brand x at least once in a given time period*

**D is the duplication coefficient which is the average observed duplications between each pair of brands divided by the overall average penetration*

Such deviations from the DoP pattern may indicate the presence of submarkets or partitions (Sharp & Sharp 1997). A submarket occurs when two or more brands share more customers with each other than expected, but still share normally with the rest of the market. On the other hand, partitions occur when two or more brands share more customers with each other, but share fewer than expected customers with the rest of the market. Partitioning is typically attributed to functional differences between brands, when customers desire a specific attribute only offered by a brand or a subset of brands. For example, the radio market shows partitioning between talk and music stations (Lees & Wright 2013). Partitioning is of particular interest to managers because it represents a group of brands that share fewer customers with competing brands outside of the partition. A brand manager should expect to gain fewer customers from these brands, or if their brand is part of a partition, can be insulated somewhat from external competition. This thesis is directly concerned with identifying whether there are groups of genres that are partitioned from the rest of the market.

To determine whether any partitions exist, the Partition Sharing Index (PSI) is used. PSI shows the level of sharing between two brands given their size. It is calculated by the following formula:

$$PSI_{ij} = \frac{Sij}{(D \times p_i)}$$

Where, S_{ij} is the observed duplication between brand *i* and brand *j*, D is the duplication coefficient (Ehrenberg et al. 2004), and p_i is the penetration of brand *i* (Sjostrom et al. 2014).

PSI can be averaged to calculate the level of sharing occurring within a group of brands, which is referred to as intra-partition sharing. It can also be used to determine the level of sharing between two groups, each containing two or more brands (inter-partition sharing). This provides an understanding of whether two groups share more or fewer customers than expected (Sjostrom et al. 2014).

A PSI of 1.0 means that the group of brands share as expected. A PSI of 1.5 means that the pair of brands share 50% more listeners than expected, while a PSI of 0.5 is 50% less than expected. Consistent with previous studies, brands sharing 20% more or less listeners (PSI ≤ 0.8 or ≥ 1.2) are considered as managerially significant deviations (Anesbury et al. 2018b; Sjostrom et al. 2014).

Since four DoP matrices contain 99 genres and an aggregation of "all other" genres, each genre was recoded into a "meta" genre following consensus among the research team (e.g. 'Hard Rock' and 'Classic Rock' are both recoded as 'Rock'). The 99 genres were recoded into 13 meta genres in order to provide an understanding of how sub-genres compete with other sub-genres from the same meta genre, in addition to how these genres share their listeners outside of the meta genre grouping. For example, it would be expected that Hard Rock and Classic Rock overshare listeners with each other, since both are sub-genres of Rock. These genres might also share fewer listeners with Electronica/Dance sub-genres such as Trance. Beyond providing an understanding of the sub-genre and meta-genre dynamic, recoding the 99 genres into 13 meta-genres enable a more feasible and tractable approach in analysis and presentation of results.

The top 99 genres were recoded to conform to the list of 13 genres used in Study Two of this thesis (see Table 7 for list of genres). These 13 meta-genres were derived primarily from (2003) short test of music preferences (STOMP). The specific meta-genres are found to account for 89% of an individual's personal music collection (Rentfrow & Gosling 2003, 2006). It was therefore deemed suitable to classify sub-genres to a respective meta-genre. See Table 7 for a list of the 13 meta-genres and Appendix section 11.1 for the sub-genre to meta-genre recode list.

The PSI matrix was sorted so that all sub-genres are grouped according to their meta genre. Intra PSIs were computed for each sub-genre grouping to indicate the degree to which sub-genres belonging to the same meta genre share listeners with each other. Inter PSIs for each sub-genre grouping are also calculated to determine the level of sharing occurring with sub-genres outside of that grouping (that is, the "rest of the market"). In addition to calculating inter PSIs between one sub-genre grouping and the rest of the market as a whole, inter PSIs are calculated between individual groupings.

Table 7: Final Genre List and Classification

STOMP Genre List (Rentfrow & Gosling 2003)	Apple Music Genre Classification	Spotify Genre Classification	FINAL LIST & CLASSIFICATION
Alternative	Alternative	Indie	Indie/Alternative
Blues	Blues	Blues	Blues
Classical	Classical	Classical	Classical
Country	Country	Country	Country
Electronica/Dance	Electronic	Electronica/Dance	Electronica/Dance
	Dance		
Folk	Folk	Folk & Americana	Folk
Heavy Metal	—	Metal	Metal
Rap/Hip-Hop	Hip-Hop/Rap	Hip-Hop	Hip-Hop/Rap
Jazz	Jazz	Jazz	Jazz
Pop	Pop	Pop	Pop
Rock	Rock	Rock	Rock
Soul/Funk	R&B/Soul	R&B	R&B/Soul/Funk
		Funk	
		Soul	
Soundtracks	Soundtrack		Soundtracks

Genres that belong to the same grouping should hypothetically overshare listeners with each other and under share with genres outside of this grouping. Therefore, using Rentfrow and Gosling's (2003) four music preference dimensions, the following proposed oversharing genres also tested are:

(1) Reflective & Complex: Classical, Jazz, Blues and Folk
(2) Intense & Rebellious: Indie/Alternative, Rock and Heavy Metal
(3) Upbeat & Conventional: Country, Pop, Religious and Soundtracks
(4) Energetic & Rhythmic: Hip-Hop/Rap, R&B/Soul/Funk, Electronica/Dance

On the other hand, the following genres that should under share listeners with each other, using Savage's (2006) findings, are:

(1) Classical with Rock and/or Electronic/Dance
(2) Country with any other genre, excluding Jazz

4. Study One Results

4.1.1. Music listening follows the general DoP pattern

Genres share listeners in line with the size of their listening base (see in Table 8). All genres share on average 96 percent of their listening base with the largest genre, Rock, 88 percent with Electronic and so on. Overall, the smallest genres, J-Rock and K-Pop, share a large proportion of their listeners with Rock and Electronic, the largest genres. Rock and Electronic share a much lower proportion of their listening base with J-Rock and K-Pop. The overall DoP pattern of sharing in line with size can be observed through the average sharing column, which declines from left to right as the size of the genre's listening base decreases.

Table 8: Sample DoP matrix of Classical dataset for Genre listening

Genre	Penetration	Rock	Electronic	Indie	Pop	Instrumental	Classic Rock	Soundtrack	Folk	Ambient	Classical	J-Rock	K-pop
Rock	78	.	80	79	77	75	75	70	70	62	53	10	6
Electronic	68	92	.	84	81	77	74	73	73	69	54	10	7
Indie	65	94	88	.	83	78	76	74	75	67	55	10	7
Pop	64	94	86	85	.	77	78	76	74	64	56	11	7
Instrumental	64	92	83	79	77	.	75	75	75	70	60	10	6
Classic Rock	61	95	82	81	81	78	.	76	75	64	58	10	6
Soundtrack	59	93	85	82	82	82	79	.	76	69	62	11	7
Folk	58	94	85	85	82	82	79	77	.	70	60	10	7
Ambient	53	91	89	82	77	85	74	77	77	.	60	10	6
Classical	48	86	76	74	74	79	73	76	72	66	.	11	7
J-Rock	8	96	85	83	86	84	77	83	70	67	68	.	21
K-pop	5	94	93	93	93	77	78	83	78	62	69	33	.
Average Sharing		96	88	86	84	85	81	80	80	74	63	14	9

The overall DoP pattern can be observed through the average sharing row, which declines from left to right in line with the penetration of each genre.

For brevity, rather than show the full 100x100 DoP matrices, Table 8 shows a subset of a DoP matrix, while Table 9 shows the average listener sharing of all brands with the largest and smallest brand in the behavioural datasets. The general pattern of sharing in line with size is broadly demonstrated by the much higher listener sharing with the largest brand (62% on average) than with the smallest bran (5% on average). The full DoP matrices (x21) can be provided upon request.

Table 9: Sharing with the largest brand compared to the smallest brand (1-year listening)

		Average listener sharing (%) with the:	
Dataset	Analysis Level	Largest brand	Smallest brand
Last.fm	Genre	95	6
	Artist	62	3
	Album	41	<1
	Song	34	1
Classical	Genre	88	9
	Artist	46	3
	Album	38	<1
	Song	39	<1
Heavy Metal	Genre	97	13
	Artist	75	1
	Album	53	<1
	Song	46	<1
Trance	Genre	95	8
	Artist	72	<1
	Album	36	<1
	Song	35	3
Indie & Alternative	Genre	98	8
	Artist	78	1
	Album	69	<1
	Song	37	<1
	Average	62	5

4.1.2. Assessing the DoP pattern with tests of fit measures

Beyond just observing the general DoP pattern, specific tests of fit can assess the applicability of law of DoP to music listening. Firstly, Pearson's correlations between average penetration and average sharing are used to assess the overall match between brand size and observed sharing. These correlations should be high and positive if duplication increases with brand size.

Table 10 below shows that Pearson's correlations are consistently high, ranging from 0.94 to 0.99. The overall average Pearson's correlation across 21 datasets is 0.98, which shows the strong relationship between brand penetration and average listener sharing.

Secondly, theoretical average duplication values estimated by the DoP formula should be similar to the observed values. This can be tested by comparing the mean absolute deviations (MADs) and mean absolute percentage errors (MAPEs). Mean absolute deviation is the average amount that a value deviates from the overall mean (Gorard 2005), while mean absolute percentage error is the amount a value deviates from the overall mean, expressed as a percentage (Armstrong & Collopy 1992). These measures should be low if the observed and expected sharing levels are similar, which indicates a good fit of the law of DoP to music listening.

As shown in Table 10, the observed and expected sharing display a close fit, as indicated by the MADs, which range from 1-5 (average MAD = 3). MAPEs between observed and expected are generally low (average MAPE = 10). However, there are some instances where the MAPE is quite high, which may indicate a departure from the fit of the law of DoP. Analyses where MAPEs are notably high will now be discussed.

Table 10: DoP tests of fit measures for 1-year music listening

Data Set	Analysis Level	Average Penetration (%)	Average Observed Duplication (%)	D-coefficient	MAD	MAPE (%)	Pearson's Correlation (Penetration and Average Observed Sharing)
Last.fm (Classical, Heavy Metal & Trance combined) (n=11,150)	Genre	29	44	1.5	4	8	0.99
	Artist	14	29	2.0	3	12	0.94
	Album	7	19	2.7	2	15	0.95
	Song	7	19	2.8	2	18	0.97
Classical (n=3,201)	Genre	31	47	1.5	4	18	0.98
	Artist	13	28	2.1	2	10	0.98
	Album	5	16	3.2	2	58*	0.97
	Song	5	16	3.5	3	46*	0.94
Heavy Metal (n=5,319)	Genre	32	46	1.4	5	10	0.98
	Artist	20	35	1.7	2	5	0.99
	Album	11	25	2.2	1	7	0.99
	Song	11	27	2.4	2	16	0.98
Trance (n=2,630)	Genre	26	43	1.6	6	14	0.98
	Artist	17	31	1.8	2	7	0.99
	Album	5	12	2.3	2	52*	0.98
	Song	5	15	2.8	2	31*	0.98
Indie & Alternative (n=15,481)	Genre	39	51	1.3	4	8	0.99
	Artist	25	40	1.6	2	5	0.99
	Album	16	31	1.9	2	7	0.99
	Song	16	34	2.1	2	7	0.98
US Survey (n=1,036)	Genre	23	32	1.4	5	5	0.98
Average	ALL	17	30	2.1	3	10	0.98

1-year music listening follows the law of DoP, as indicated by the tests of fit measures.

4.1.3. Higher MAPEs for albums and songs may be due to lower brand penetrations

Mean absolute percentage errors (MAPEs) are notably higher for albums and songs in the Classical and Trance datasets (as high as 58%). This may be a result of the lower brand penetrations for these two analyses, which is on average 5%. Some of the lower penetration brands share fewer listeners than expected for their size, which is likely an outcome of the smaller overall listening base, and therefore attributable to random

sampling variation. For example, some albums or songs have fewer than 10 listeners. As albums and songs contain as many as 3.6 million brands, these very small brands still appear in the largest 99 counts by penetration. A known weakness of MAPE is that it is more sensitive (i.e. produces higher values) when the expected values exceed the observed values than when the expected values underestimate the observed values (Armstrong & Collopy 1992). Given that penetration is a key input in estimating the expected sharing, MAPEs are higher for the lower penetration brands (Wright et al. 2002), which impacts the overall assessment of fit. Due to this weakness, the data is reanalysed using only brands above a minimum penetration level to determine if the MAPE improves.

As shown in Table 11, the MAPEs are superior when very small brands are excluded (≥10%). The average MAPE in this analysis is 6% (a 4% decrease from analysis not excluding small brands). Pearson's correlation between penetration and average duplication is 0.92 on average, which is still a good fit despite being a slight decrease from r=.98. The average MAD of 3 also indicates a very small difference between observed and theoretical average duplications. Overall, including only brands above a minimum of 10% penetration notably reduces the MAPE. However, Pearson's correlations are slightly lower, especially for song (0.80 on average). This is due to fewer brands reaching ≥10% penetration criteria and therefore a smaller sample of brands.

Table 11: Average Tests of Fit across 21 datasets for the law of Duplication of Purchase (1-year) excluding brands below a minimum penetration level.

Analysis Level	Minimum Penetration (%)	Average Penetration (%)	Average Observed Duplication (%)	D-coefficient	MADs	MAPE (%)	Pearson's Correlation (Penetration and Average Observed Sharing)
Genre	≥20	39	52	1.4	4	8	0.98
Artist	≥20	26	45	1.7	2	5	0.96
Album	≥10	14	34	2.4	2	6	0.92
Song	≥10	13	37	3	3	7	0.80
Average	—	23	42	2.1	3	6	0.92

Tests of fit measures are improved excluding low penetration brands.

4.1.4. Tests of fit: Applying the law of Duplication of Purchase to shorter durations

It is possible that the DoP analysis in this thesis may be using too long a time period (12 months of listening). The number of category buyers, who buy any brand at least once, is dependent on the length of analysis period (Ehrenberg et al. 2004). Therefore, a longer time period results in more listeners of any brand, and the reverse for a shorter time period. With a one-year time period, there is more opportunity for an eclectic and vast range of genres, artists, albums and songs to be consumed. A large genre such as Rock and a small genre like K-Pop are more likely to be listened to by the same listener

within the same yearly time period than they are in a shorter time period. The same applies to an artist, album or song.

The time period of analysis may affect a number of tests of fit. In particular, individual brand penetrations (the number of listeners who have listened to that particular brand at least once in the analysis period) and the average duplication (the proportion of listeners of brand X, who also listened to brand Y in the given analysis period) are likely to be impacted by the time period of analysis. In a longer period, more listeners are more likely consume a particular brand (higher penetration), in addition to listening to many other brands (higher average duplication). Brand penetrations, are however, calculated relative to the size of the overall market (total number of listeners of any brand in a given time period) (Ehrenberg et al. 2004). Thus, the overall measure of fit may not necessarily be affected.

Nonetheless, the fit of the law of DoP is retested on the Last.fm dataset (consisting of the Classical, Heavy Metal and Trance datasets merged), using differing time periods. Specifically, time periods of 6-months and 3-months are assessed. Both 6-monthly and all four 3-monthly time periods were examined. One random 1-month and 1-week slice of the data was also examined to extend the generalisability. Analysis only includes brands that reach above a penetration cut-off (noted in Table 12) to reduce the effects of random sampling variation.

4.1.5. The law of DoP holds across differing time periods

Music listening at genre, artist, album and song level, follows the law of DoP at 6-month, 3-month, monthly and weekly time periods (Table 12). The overall average MAD is 3, the MAPE is 16 (%) and the Pearson's correlation is 0.90, which demonstrates a good fit of the Law. There is a large degree of similarity in the D-coefficients across time periods, which indicates stability in sharing and hence music listening. For example, at the genre level, D-coefficients are 1.4 for 6-month, 3-month and 1-month time periods, and 1.5 for a 1-week time period.

Table 12: Average DoP Tests of Fit for 6-month, 3-month, 1-month and 1-week listening.

Time Period	Penetration Cut-Off (%)	Analysis Level	Average Penetration (%)	Average Observed Duplication (%)	D-Coefficient	MADs	MAPE (%)	Pearson's Correlation (Penetration and Average Observed Sharing)
6-months	≥20% pen	Genre	38	53	1.4	4	8	0.98
	≥10% pen	Artist	19	35	1.9	3	11	0.93
	≥10% pen	Album	10	23	2.3	2	10	0.96
	≥10% pen	Song	12	34	2.8	4	14	0.77
		Average	19	36	2.1	3	11	0.91
3-months	≥20% pen	Genre	35	49	1.4	4	8	0.98
	≥10% pen	Artist	16	32	2	3	12	0.91
	≥5% pen	Album	9	21	2.6	3	14	0.92
	≥5% pen	Song	8	22	2.8	3	13	0.89
		Average	17	31	2.2	3	12	0.92
1-month	≥20% pen	Genre	32	46	1.4	3	5	0.98
	≥10% pen	Artist	13	31	2.4	4	16	0.79
	≥5% pen	Album	7	19	2.9	4	22	0.58
	≥5% pen	Song	7	30	4.3	5	22	0.88
		Average	15	31	2.7	4	16	0.81
1-week	≥20% pen	Genre	30	43	1.5	3	6	0.97
	≥5% pen	Artist	7	22	3.2	3	25	0.84
		Average	18	33	2.4	3	16	0.90
		Average	18	33	2.4	3	16	0.90

The law of DoP continues to hold across shorter time periods.

4.2. Do partitions and submarkets exist?

While the law of DoP may broadly hold, occasionally a group of brands compete more or less closely with each other than with the rest of the market. Submarkets are typically secondary to main pattern of sharing in line with size, while partitioning indicates the presence of market segmentation. Submarkets and partitioning are commonly the result of functionality, as a subset of brands may offer customers a particular attribute they desire, while brands outside of the grouping may not fulfil these functional requirements (Kalwani & Morrison 1977; Lees & Wright 2013).

This section reports evidence of genre submarkets and partitioning for a year of music listening. Intra and inter partition sharing indices (PSI) are used to determine whether any submarkets or partitions are present. Intra PSI indexes how sub-genres belonging to the same meta-genre share listeners with each other (e.g., how Soft Rock and Classic Rock share listeners with each other under the Rock meta-genre). Inter PSI shows how this group of sub-genres share listeners with any other genre (e.g., Rock sub-genres with all other genres in the market). In line with previous research

(Anesbury et al. 2018b; Sjostrom et al. 2014), genres are considered partitioned when the intra PSI is ≥1.2 and the inter PSI is ≤0.8.

4.2.1. Genres are not partitioned from the rest of the market

As previously described, sub-genres were recoded into their respective meta-genre to conform with the list shown in Table 7 after consensus among the research team. For example, Classic Rock, Hard Rock and Soft Rock are grouped into a Rock meta-genre. Sharing with other Rock sub-genres (e.g. Classic Rock with Hard Rock) and with genres outside of the Rock meta-grouping (e.g. Classic, Hard and Soft Rock with Jazz sub-genres) is then calculated.

Table 13 shows that while sub-genres do share overshare listeners with sub-genres belonging to the same meta genre grouping i.e. Soft Rock with Classic Rock, sub-genres are not partitioned from the rest of the market. For example, Blues sub-genres share on average 60% more listeners with each other, as indicated by the 1.6 intra PSI. However, the inter PSI of 1.1 indicates that Blues sub-genres share 10% more listeners than expected for their size with genres outside of the Blues grouping. As PSIs are considered as partitioned when the inter PSI is 0.8 or below, Blues sub-genres are not isolated and exhibit normal sharing outside of the grouping (i.e. they are not partitioned from the rest of the market). On average, sub-genres part of the same meta-genre grouping share 20% more listeners than expected with each other (intra PSI = 1.2), but share with any genre outside of the grouping directly proportional to their penetration (inter PSI = 1.0). Therefore, no meta-genre is isolated from the market with penetration dictating the likelihood of listening to a second genre.

Table 13: Sharing within and outside of a meta genre for five behavioural datasets (1-year listening)

Dataset:	Classical		Heavy		Indie		Trance		Last.fm		Average	
Genre	Intra	Inter	Intra	Inter	Intra	Inter	Intra	Inter	Intra	Inter	Intra	Inter
Blues			1.6	1.1	1.5	1.1				1.0	1.6	1.1
Classical	0.9	0.9		1.2		1.0		1.1	1.0	1.0	1.0	1.1
Country				1.1		1.0		1.1		1.0		1.1
Electronica/Dance	1.1	1.0	1.6	1.1	1.2	1.0	1	1	1.0	1.0	1.2	1.1
Folk	1.0	1.0	1.5	1.1	1.0	0.9	1.3	1.1	1.0	1.0	1.2	1.0
Hip-Hop/Rap	1.2	1.0	1.5	1.1	1.0	1.0	1	1	1.0	1.0	1.1	1.1
Indie/Alternative	1.0	1.0	1.1	1.1	0.9	1.0	1	1.1	1.0	1.0	1.0	1.1
Jazz	1.2	1.1		1.1	1.2	1.1		1.1		1.0	1.2	1.1
Metal	1.5	1.1	1.1	1	2.0	1.0	2.3	1.1	1.0	1.0	1.6	1.0
Pop	1.2	1.1	1.3	1.1	1.0	1.0	1.3	1.1	1.0	1.1	1.2	1.1
R&B/Soul/Funk	1.3	1.0	1.7	1.1	1.2	1.0	1.2	1	1.0	1.1	1.3	1.1
Rock	1.1	1.1	1.1	1.1	1.0	1.0	1.4	1.2	1.0	1.1	1.1	1.1
Soundtracks	0.9	0.9	0.9	0.9	1.0	1.0	1.1	1	1.0	0.9	1.0	1.0
Average	1.1	1.0	1.3	1.1	1.2	1.0	1.3	1.1	1.0	1.0	1.2	1.0
Overall	1.2 Intra PSI						1.0 Inter PSI					

4.2.2. Similar genres overshare listeners

Meta-genre groupings (e.g. Classical sub-genres grouped) listener sharing with a second sub-genre grouping (e.g. Jazz sub-genres grouped) was examined for a pair of genres that are reported to have overlapping listening bases (Rentfrow & Gosling 2003).

Table 14 shows inter PSIs (listener sharing outside of a grouping) for proposed oversharing genre groups. On average, genre groupings that are proposed to over share listeners with each other, do so by 20% (inter PSI = 1.2). Some notably large instances of oversharing between two genre groupings occurs in the Survey dataset. For example, Jazz and Blues share 160% more listeners with each other than expected (inter PSI = 2.6) while Folk and Blues share 120% (2.2 inter PSI) more listeners. On average, 9 out of the 15 proposed groupings overshare listeners (inter PSIs overall average is 1.2). However, groupings inconsistently overshare across different datasets as less than half of all groupings have an inter PSI ≥1.2 across the 6 datasets (47/105 = 45%). Broadly, the proposed genre groupings do share more than expected, which may indicate functional similarity between pairs of genres.

Table 14: Inter PSIs for proposed oversharing genres (1-year music listening).

Meta-genre grouping		Inter PSI						
Genre 1 shares with:	Genre 2	Dataset Classical	Heavy	Indie	Trance	Merged	Survey	Average
Classical	Jazz	1.0	1.4	1.1	1.2	1.2	1.5	1.2
Classical	Blues	0.9	1.2	1.1	N/A	1.1	1.2	1.1
Classical	Folk	0.9	1.3	1.0	1.2	1.1	1.6	1.2
Jazz	Blues	1.2	1.3	1.2	N/A	1.2	2.6	1.5
Jazz	Folk	1.1	1.3	1.0	1.2	1.2	1.8	1.3
Folk	Blues	0.9	1.2	1.0	N/A	1.2	2.2	1.3
Metal	Rock	1.2	1.0	1.2	1.5	1.0	1.2	1.2
Metal	Indie/Alt	1.0	0.9	0.9	1.1	0.9	1.7	1.1
Rock	Indie/Alt	1.0	1.1	1.0	1.2	1.1	1.1	1.1
Country	Pop	1.1	1.3	1.1	1.4	1.3	0.8	1.2
Country	Soundtracks	0.9	1.0	1.0	1.1	1.0	0.8	1.0
Pop	Soundtracks	1.0	1.0	1.0	1.1	1.0	1.1	1.0
Hip-hop/Rap	R&B/Soul/Funk	1.2	1.4	1.1	1.0	1.1	1.5	1.2
Hip-hop/Rap	Electronica	1.1	1.5	1.1	0.9	1.2	1.4	1.2
Electronica	R&B/Soul/Funk	1.1	1.4	1.1	0.9	1.1	1.2	1.1
Average (Overall)		1.2						

Most proposed oversharing genres do share more listeners than expected.

4.2.3. Genres are not partitioned from the market

Pairs of genres that should share fewer listeners than expected were also investigated in order to determine whether any genre attracts a distinct segmented listening base. The genre pairings were formed based on findings in music studies, which suggests that two distinct listening bases should exist (Savage 2006). For example, Classical and Electronica/Dance should share fewer listeners with each other than expected. A genre is considered to be partitioned when the inter PSI is ≤ 0.8, which indicates under sharing of 20% or more.

Table 15 shows sharing across genre groupings (inter PSI) for 3 genre pairings. On average, the genres share listeners directly proportional to their penetration, which is in line with the law of DoP (Average inter PSIs range from 1.0-1.1). One isolated instance where two genres meaningfully under-share listeners occurs between Classical and Rock in the Survey data (inter PSI = 0.8). However, these two genres do not consistently share fewer listeners than expected, and in some datasets, share up to 20% more listeners. The finding that Classical and Rock do not attract unique listeners, is consistent with Peterson and Kern's (1996) "cultural omnivore" findings where listeners enjoy both highbrow (Classical) and lowbrow (Rock) genres. Overall, genres share as expected with each other, despite the suggestion that some genres should not share listeners with each other due to differences in preferences (Savage 2006).

Table 15: Inter PSIs for proposed under sharing genres (1-year music listening).

Meta-genre grouping		Inter PSI						
Genre 1 shares with:	Genre 2	Dataset						
		Classical	Heavy	Indie	Trance	Merged	Survey	Average
Classical	Rock	0.9	1.2	1.0	1.2	1.0	0.8	1.0
Classical	Electronica/Dance	0.9	1.5	1.1	1.0	1.1	1.1	1.1
Country	Metal	0.9	0.9	1.0	1.2	0.9	0.9	1.0

Proposed under sharing genres are not partitioned.

5. Study Two Method

5.1. Are music genre profiles different?

Study Two examines the listener profiles of 13 genres to determine the extent to which they are similar or different. Specifically, this study is a differentiated replication of brand user-profile research, which finds that competing brands attract a very similar type of customer in terms of demographic, psychographic and media usage variables (Hammond et al. 1996; Uncles et al. 2012).

5.2. Data

To investigate the degree of similarity between genre listener profiles, survey data was collected through an online survey in the United States during February 2019. Survey data was necessary due to the lack of psychographic and complete demographic information in the Last.fm data used in Study One. The final data consists of a nationally representative US sample by age, gender, race and location (refer to Table 4) (n = 1036, age range from 18 to 84, mean age = 48.6, SD = 17.6). Participants were recruited via Toluna, a commercial panel provider (Toluna Influencers n.d.). The survey took approximately 15 to 20 minutes to complete and was hosted by Toluna. Strict quotas and screening questions were set to ensure the data captured a representative sample of the US population. For ethics purposes, subjects were required to be aged 18+ in order to participate. In addition, respondents were required to have listened to music of their choosing in the past week to ensure that they are regular music listeners.

5.2.1. Demographic and psychographic variables tested

Once respondents agree to participate and pass the screening questions, they are required to answer a number of demographic questions pertaining to age, gender, state of residence and social class factors. In line with ethical research conduct, respondent confidentiality is maintained. In order to investigate the link between psychographics and music listening, respondents also completed a short personality test (see section 5.2.3. for more detail). The full survey appears in the Appendix, section 11.2.

5.2.2. Music genre usage

Music genre listening in the past week forms the key usage variable in this study. Genres have previously been used to examine the relationship between music preference and demographic and psychographic variables (e.g. Peterson & Kern 1996; Rentfrow & Gosling 2003; Savage 2006). However, prior studies typically measure different genres and use different classifications. For example, Savage (2006) uses nine genres excluding Pop, while North (2007c) uses 19 genres including four variations of Pop. Rentfrow and Gosling (2003) generated a Short Test of Musical Preferences (STOMP), which consists of 14 genres that load onto four music dimensions. These dimensions are: (1) reflective and complex (Classical, Jazz, Blues and Folk), (2) intense and rebellious (Alternative, Rock and Heavy Metal), (3) upbeat and conventional (Country, Pop, Religious and Soundtracks), and (4) energetic and rhythmic (Rap/Hip-Hop, Soul/Funk and Electronica/Dance). The final list of genres used in this study includes classifications that are similar to STOMP (Rentfrow & Gosling 2003), Apple

Music and Spotify. Research finds that respondents have a high level of familiarity (97%) with these genre classifications and that these particular genres account for 89% of an individual's music collections (Rentfrow & Gosling 2003, 2006).

5.2.3. Measuring personality to capture psychographic profiles

The 'Big Five' personality dimensions are a taxonomy of personality traits enabling researchers to study the specified domains of personality, rather than the infinite attributes that differ between individuals (John & Srivastava 1999). These five dimensions are consistently found to describe personality aspects (Goldberg 1992). The five traits, known as the big five, are openness, conscientiousness, extraversion, agreeableness and neuroticism (Goldberg 1981). These five traits have been widely used as measures of personality (see Goldberg 1992; Thalmayer et al. 2011).

Music studies report that tastes for specific genres differ based on big five personality traits (e.g. Greenberg et al. 2016; Rawlings & Ciancarelli 1997). However, due to inconsistent findings in personality correlations (Delsing et al. 2008; Rentfrow & Gosling 2003) and contrary evidence that psychographic brand user profiles seldom differ (e.g. Patrick et al. 2016), personality genre profiles are re-examined. Consequently, a Big Five personality scale was used to examine genre personality profiles.

As personality is one of many variables measured in the 20-minute survey, Rammstedt & John's (2007) widely accepted and validated Big Five Inventory-10 (BFI-10) is used (Rammstedt 2007; Rammstedt et al. 2013). BFI-10 is a shorter 10-item version of the larger Big Five 44-item Inventory (Rammstedt & John 2007). Although the BFI-10 comprises less than 25% of the full BFI-44 scale, the 10-item scale has predictive ability similar to the 44-item scale, and requires a minimum amount of participant time, which curtails respondent fatigue and boredom (Burisch 1984; Thalmayer et al. 2011).

The BFI-10 consists of 10 statements designed to capture aspects of an individual's personality traits. Two statements each directly measure one of the Big Five Personality traits: openness, conscientiousness, extraversion, agreeableness and neuroticism. Each statement is assessed on a five-point scale ranging from 1: Disagree Strongly, to 5: Agree Strongly, including a midpoint at 3: Neither Agree Nor Disagree. The full list of statements is shown in Table 16.

Table 16: Personality statements

Instruction: How well do the following statements describe your personality?						
I see myself as someone who…		1 Disagree Strongly	2	3 Neither agree nor disagree	4	5 Agree Strongly
1	…is reserved					
2	…is generally trusting					
3	…tends to be lazy					
4	…is relaxed, handles stress well					
5	…has few artistic interests					
6	…is outgoing, sociable					
7	…tends to find fault with others					
8	…does a thorough job					
9	…gets nervous easily					
10	…has an active imagination					

5.2.4. Measuring hedonic & eudaimonic motivations for music listening

On an individual level, music can be consumed for a number of different motivations. Such motivations include to relieve boredom, for pleasure or enjoyment, self-expression and to obtain more complex and meaningful fulfillment (Lonsdale & North 2011; North et al. 2000; North et al. 2004). Oliver and Raney (2011) previously tested hedonic and eudaimonic motivations for viewing films. Hedonic motivations are defined as the fulfilment of pleasure or enjoyment, while eudaimonic motivations are defined as pursuing deeper and more meaningful enjoyment. Statements on the scale were initially generated following a survey of 141 undergraduate students, which were then factor analysed. Items with low sampling adequacy, loaded on multiple factors, were overly redundant and had low commonalities were removed. Convergent and discriminant validity revealed a good fit for the two-factor structure. Consequently, Oliver and Raney's (2011) scale is used to examine music listening motivations. As the original scale was used to correlate motivations to film genre preferences, statements are modified to be contextually appropriate for music listening.

Respondents were asked to indicate the extent to which 12 statements accurately reflected their motivations for listening to music on the same 7-point scale, ranging from 1 (Strongly Disagree) to 7 (Strongly Agree) with a neutral point at 4, used by Oliver and Raney (2011). Statement numbers 1 to 6 assess eudaimonic motivations, while 7 to 12 assess hedonic motivations. The full list of statements appears in Table 17. Note that American-English spelling is used to correspond with sampling.

Table 17: Hedonic and Eudaimonic Motivation Statements

How well do each of these statements reflect your music preferences?	
Original Statement	**Modified Statement**
I like movies that challenge my way of seeing the world.	I like music that challenges my way of understanding the world.
I like movies that make me more reflective.	I like music that makes me more reflective.
I like movies that focus on meaningful human conditions.	I like music that focuses on meaningful human conditions.
My favorite kinds of movies are ones that make me think.	My favourite types of music make me think.
I am very moved by movies that are about people's search for greater understanding in life.	I am very moved by music that is about people's search for greater understanding in life.
I like movies that have profound meanings or messages to convey.	I like music that has profound meanings or messages to convey.
It's important to me that I have fun when watching a movie.	It's important for me to have fun when listening to music.
Movies that make me laugh are among my favorites.	Music that makes me smile are among my favourites.
I find that even simple movies can be enjoyable as long as they are fun.	I find that even simple music can be enjoyable as long as it is fun.
I like movies that may be considered ''silly'' or ''shallow'' if they can make me laugh and have a good time.	I like music that may be considered "silly" or "shallow" if it can make me smile and have a good time.
For me, the best movies are ones that are entertaining.	For me, the best music is entertaining.
My favorite kinds of movies are happy and positive.	My favorite type of music is happy and positive.

5.3. Analysing demographic genre listener profiles

To analyse genre listener profiles, the method used originally by Hammond and colleagues (1996), in addition to Kennedy and Ehrenberg (2001a) and others (e.g. Anesbury et al. 2017), which compares each brand's profile to the average profile of the category is drawn upon. The rationale for this method of analysis is that evidence of any meaningful segmentation should be apparent without the use of sophisticated analysis procedures (Hammond et al. 1996). Studies using this technique demonstrate that directly competing brands rarely differ in their profiles, across a number of different product categories, countries and contexts (e.g. Anesbury et al. 2018a; Dawes 2009; Patrick et al. 2016; Uncles et al. 2012).

5.4. Preparing data for analysis

Firstly, for each genre, crosstabulations are produced for all demographic variables. For example, how many of Rock's listeners earn $30,000 USD or less in a year? These raw counts are converted into a percentage of that genre's listening base. For example, of the total 538 listeners of Rock, 127 have an income of less than $29,999 a year, which is 24% of Rock's total listening base. Column averages are then calculated for each variable, which represents the 'average' genre or expected profile. The data now appears in the form presented in Table 18.

Table 18: Example of genre's personal income profiles as percentages

	Annual Personal Income in USD (%)						
Genre	≤$29,999	$30k-$49,999	$50k-$69,999	$70k-$89,999	$90k-$124,999	$125k-$199,999	≥$200k
Rock	24	22	17	12	11	7	4
Pop	21	19	17	12	12	8	5
Country	30	19	16	10	10	7	3
Hip-Hop/Rap	28	21	30	11	11	5	3
R&B/Soul/Funk	28	22	17	10	12	3	4
Classical	24	13	17	14	13	6	8
Average	26	19	19	12	11	6	5

5.4.1. Calculating deviations from the average genre profile

To understand the degree of similarity between genres, deviations of each genre's profile from the average of all profiles are calculated. This is done by subtracting the percentage of each genre's listening base from the average profile of all genres. In this example, the proportion of Rock listeners who earn ≤$29,999 USD in a year is 2 percentage points less than the average of all genres (as shown in Table 19).

Table 19: Example of Deviations and Mean Absolute Deviations

	Annual Personal Income in USD						
Genre	≤$29,999	$30k-$49,999	$50k-$69,999	$70k-$89,999	$90k-$124,999	$125k-$199,999	≥$200k
Rock	-2	2	-2	0	-1	1	0
Pop	-5	0	-2	1	1	2	0
Country	4	0	-3	-1	-2	1	-1
Hip-Hop/Rap	3	1	**11**	0	-1	-1	-1
R&B/Soul/Funk	2	3	-2	-1	1	-3	-1
Classical	-2	-6	-2	2	1	0	4
MAD	3	2	4	1	1	1	1

5.5. Which differences are considered noteworthy?

Interpretation of the differences between genres rests on the threshold at which individual deviations are considered managerially significant. Brand user-profile studies have used deviations of 5, 6, or 10 percentage points (pp hereon) as the level that brand differences are regarded as managerially significant (e.g. Anesbury et al. 2017; Kennedy & Ehrenberg 2001a; Nelson-Field & Riebe 2011). Deviations below 6 pp are said to be negligible while those below 5 pp indicate effectively no difference and may reflect random variation (Hammond et al. 1996; Kennedy et al. 2000). Therefore, in line with Kennedy and Ehrenberg (2001a), Anesbury et al. (2018) and Winchester and Lees (2016) deviations ≥ 10 pp are considered managerially significant and appear in bold in tables of results.

Once individual deviations are calculated, Mean Absolute Deviations (MADs hereon) are used to summarise the deviation level for each variable. Given that a weakness of MADs is that data at the tails can impact the average value by minimising the size of some larger differences (Nelson-Field & Riebe 2011), the percentage of deviations that exceed 10-pp and 5-pp are also reported. It is noted that the selection of a deviation threshold is arbitrary and will alter the interpretation of results. Therefore, in the absence of multiple deviations fulfilling the 10-pp or 5-pp criterion, individual cases of note are discussed. An example of a table of results is shown below in Table 20.

Table 20: Example of genre profile results table

	Annual Personal Income in USD						
Genre	≤$29,999	$30k-$49,999	$50k-$69,999	$70k-$89,999	$90k-$124,999	$125k-$199,999	≥$200k
Rock	-2	2	-2	0	-1	1	0
Pop	-5	0	-2	1	1	2	0
Country	4	0	-3	-1	-2	1	-1
Hip-Hop/Rap	3	1	**11**	0	-1	-1	-1
R&B/Soul/Funk	2	3	-2	-1	1	-3	-1
Classical	-2	-6	-2	2	1	0	4
MAD	3	2	4	1	1	1	1
% of deviations ≥ 5 pp	7						
% of deviations ≥ 10 pp	2						

**note: not a table of results

5.6. Personality profiles analysis

The following outlines the method required to analyse psychographic profiles obtained from Rammstedt & John's (2007) BFI-10 item scale. Firstly, scores for all respondents are calculated for each Big Five personality trait. This is achieved by adding the scores from the 5-point scale for the following statement numbers:

Extraversion: Statement number 1R & 6
Agreeableness: Statement number 2, 7R

Conscientiousness: Statement number 3R, 8
Neuroticism: Statement number 4R, 9
Openness: Statement number 5R, 10
(*R = item is reverse-scored)* (Rammstedt & John 2007)

Refer to Table 16 in section 5.2.3 for statements.

For each genre, crosstabulations are computed for all Big Five traits. For example, 27 of Rock's listeners scored 2 for Extraversion, 25 scored 3 for Extraversion and so on. As each trait is calculated from two statements, the minimum raw score is 2 and the maximum is 10. Individual scores are then standardised by subtracting the mean overall score for each personality trait and dividing by the standard deviation. This procedure is commonplace in psychological research (see Fischer & Milfont 2010; Kim & Ferree Jr 1981) and when analysing scales (Hemming 2013; Holbrook & Schindler 1989).

Table 21: Descriptive statistics for Big Five personality trait raw scores

Big five personality trait	Mean personality trait score	Standard deviation
Openness	6.9	1.8
Conscientiousness	7.8	1.8
Extroversion	6.0	1.9
Agreeableness	7.3	1.8
Neuroticism	5.4	2.2

To analyse whether genre listening differs by BFI personality traits, Hammond et al.'s (1996) method of comparing each genres' profile to the average profile of the category is used as it was for demographic variables. Consistent with demographic variable analysis, the percentage of deviations that exceed both 10-pp and 5-pp are reported, while deviations ≥10 pp are bolded.

5.6.1. Classifying Personality Scores

Differing spectrums of personality trait scores are separated in different analyses to avoid comparing, for example, high and low scorers of Extraversion. Two different methods of analyses are therefore employed for personality analysis. Firstly, the mean raw score of each genre's listeners for all five personality traits are compared to mean raw overall trait score, which includes listeners of any genre. For example, if the mean score for Metal listeners is 6.5 for Neuroticism, this deviates from the average Neuroticism score of 5.4 by 1.1 pp. This analysis demonstrates how much the average genre listener's personality trait differs from the average overall personality trait.

The second method of personality analysis categorises listeners into groups of high, medium, and low scores by personality trait, based on standardised scores, rather than raw scores. This is to provide the most possible chance of finding differences, in that it essentially eliminates the potential effect of having a large number of people scoring similarly, and reducing the differences in means in the first analysis. The following classifications for standardised scores are:

High personality trait scorers — classified as scoring ≥1 standard deviation above the mean

Mid personality trait scorers — classified as scoring ≥-1 & ≤ 1 standard deviation from the mean

Low personality trait scorers — classified as scoring ≤ -1 standard deviation below the mean

5.7. Hedonic and eudaimonic motivation profiles analysis

Hedonic and eudaimonic motivations for listening are analysed using a similar classification method as personality profile analysis. However, rather than use all 6 statements that assess either hedonic or eudaimonic music listening motivations, the average score for these two dimensions is used. Firstly, the average raw score of the six hedonic and eudaimonic motivation statements is calculated to provide one score for both dimensions per respondent. This score is then standardised by subtracting the mean and dividing by the standard deviation. Respondents are classified into high, low and mid motivation scorers using the same classifications as personality analysis. Crosstabulations between high, low and mid motivation scorers and listeners of each genre are then calculated. For example, the number of Blues listeners who score ≥ 1 standard deviation. Deviations from the average profile are then calculated. The percentage of deviations ≥ 5 pp and ≥ 10 pp are reported and deviations ≥ 10 pp are bold. An example of a results table for motivations for music listening is shown in Table 22. It is acknowledged that a five-point scale is used for personality (Rammstedt 2007), whereas a seven-point scale is used for music listening motivations. However, this decision was made in order to uphold consistency with the original motivation scale (Oliver & Raney 2011).

Table 22: Example of motivation profile analysis for hedonic motivations for music listening.

	Hedonic Motivations		
Genre	Low	Mid	High
Rock	-6	-6	-5
Pop	-3	-3	-3
Country	-6	-8	-4
Hip-Hop/Rap	0	**10**	1
MADs	4	7	3

**note: not a table of results

5.8. Prevalence of genre listening

As shown in Table 23, genres range in the number of past weekly listeners. While all genres contain a sufficient listening base size for analysis, crosstabulation counts that consist of fewer than 20 respondents are not included in the calculation of the average and are excluded from analysis (and appear in tables as "—").

Table 23: Prevalence of genre listening in the past week (US survey data n=1,036).

Genre	% of Listeners (Past Week)	Number of listeners (Past Week)
Rock	52	538
Pop	46	477
Country	39	404
Hip-Hop/Rap	31	321
R&B/Soul/Funk	28	289
Classical	22	229
Metal	18	188
Soundtracks	18	187
Indie/Alternative	17	178
Jazz	16	166
Blues	16	162
Electronica/Dance	14	140
Folk	10	106

Rock and Pop are the most listened to genres in the past week.

6. Study Two Results

6.1. Some genre listener differences by gender

As shown in Table 24, some genres attract a higher proportion of female or male listeners than compared to the average genre's gender profile. Most notably, more females (+10 pp) and fewer males (-10 pp) listen to Pop than compared to the average genre profile. Conversely, more males than females listen to Metal and Blues (10 pp). Further research is required to understand why these larger differences might occur. However, this is beyond the scope of this thesis. Other larger deviations occur for Country, Hip-Hop/Rap, R&B/Soul/Funk, where more females and fewer males listen to these genres (8 pp). On the other hand, more males and fewer females listen to Electronica/Dance (9 pp). A further eight genres deviate by 5-pp or more, which indicates some gender listening differences. It should be noted that the most any genre deviates is by 10-pp and although ten other cases are close to this threshold, it would be difficult to profile most genres as purely male or female.

Table 24: Genre listener profiles are predominantly similar by gender

Genre	Male	Female
Rock	2	-2
Pop	**-10**	**10**
Country	-8	8
Hip-Hop/Rap	-8	8
R&B/Soul/Funk	-8	8
Classical	6	-6
Metal	**10**	**-10**
Soundtracks	-9	9
Indie/Alternative	-1	1
Jazz	5	-5
Blues	**10**	**-10**
Electronica/Dance	8	-8
Folk	4	-4
MAD	7	7
% of deviations ≥ 5 pp	77	
% of deviations ≥ 10 pp	23	

Most gender differences are small, although some genres attract slightly more gender listeners than compared to the average.

6.2. Some genres attract listeners of different ages

Table 25 shows the deviations for four age groups of genre listeners. There are some large differences observed, especially among the 55+ year old age group. Country, Classical, Jazz, Blues and Folk attract more listeners aged 55+ than the average genre profile (10 to 14 pp deviations). Many of these genres have been profiled by previous research as 'old people' genres (North & Hargreaves 2007c). Notably fewer 55+ year old listeners appear in the listening bases of Hip-Hop/Rap, Metal, Indie/Alternative and Electronica/Dance (deviations up to -21). A few larger deviations occur among 25-39-year-old listeners. Far more listeners from this age group listen to Electronica/Dance (+22 pp) and Hip-Hop/Rap. However, this age group is less represented in Country's listening base (-10 pp). In total, 56% of deviations are 5 pp or more and 23% are 10 pp or more. This suggests that different genres may attract a different aged listener, which is consistent with radio station audience research (Nelson-Field & Riebe 2011; Winchester & Lees 2013).

Table 25: Genre listener profiles by age group

Genre	18-24	25-39	40-54	55+
Rock	-5	-7	6	6
Pop	-1	-1	3	-1
Country	-6	**-10**	3	**13**
Hip-Hop/Rap	8	**10**	1	**-19**
R&B/Soul/Funk	1	2	2	-5
Classical	-3	-6	-5	**14**
Metal	4	0	8	**-12**
Soundtracks	2	1	-2	-1
Indie/Alternative	5	2	4	**-11**
Jazz	-4	-5	-5	**13**
Blues	-5	-4	-2	**10**
Electronica/Dance	6	**22**	-8	**-21**
Folk	-3	-4	-6	**14**
MAD	4	6	4	**11**
% of deviations ≥ 5 pp	56			
% of deviations ≥ 10 pp	23			

Some larger age differences are evident between the listening bases of genres.

6.3. Genre listening by ethnic group

As shown in Table 26, genres are generally similar in the ethnic background of their listeners. Some larger deviations are observed for listeners of R&B/Soul/Funk, where there are 20 pp fewer Caucasian or White listeners and 18 pp more African-

American or Black listeners compared to the average genre's ethnic profile. Another noteworthy deviation occurs for Hip-Hop/Rap which is listened to by more African-American or Black listeners and fewer Caucasian or White listeners. Rock, Country and Folk are genres that are listened to by more Caucasian or White listeners than the average genre. The MAD of 7 for Caucasian or White and African-American or Black listeners may indicate some ethnic differences in genre listening. However, given that almost three quarters of deviations fall below 5 pp and 85% fall below 10 pp, ethnic differences are predominantly small.

Table 26: Genre listener profiles by stated ethnic background

Genre	Caucasian or White	African-American or Black	Hispanic/Latino/ Spanish	Other*
Rock	**10**	-7	-2	-3
Pop	1	-3	1	-1
Country	12	-7	-3	-4
Hip-Hop/Rap	**-13**	**10**	4	-1
R&B/Soul/Funk	**-20**	**18**	2	0
Classical	3	-3	-2	3
Metal	9	-8	2	-3
Soundtracks	-2	1	-1	4
Indie/Alternative	2	-3	1	0
Jazz	**-10**	8	-2	1
Blues	-2	6	-3	1
Electronica/Dance	-1	-4	4	1
Folk	**13**	-8	-3	1
MADs	7	7	2	2
% of deviations ≥ 5 pp	29			
% of deviations ≥ 10 pp	15			

Most genres attract listeners from similar ethnic backgrounds, with some exceptions.
**other includes Asian, American-Indian, Alaskan and Native Hawaiian or Pacific Islander

6.4. Listening to genres by annual personal income

Table 27 shows that genres attract a very similar type of listener in terms of annual personal income (USD). Only 7% of deviations are 5 pp or greater than the average while no such deviation is greater that 7 pp. These slightly larger deviations occur for Country, who's listeners are slightly more likely to be in the lowest income group (-5 pp), Jazz, whose listeners are slightly more likely (6 pp) to earn between $90,000 and $124,999 annually, and Folk, whose listeners are less likely to be in the $30,000 to $49,000 (-7 pp) and $70,000 to $89,999 (-6 pp) income groups. However, the low incidence of noteworthy deviations, in addition to the low overall MADs of 1-3 pp, demonstrate that no genre is especially listened to more or less by a specific type of listener based on their annual personal income.

Table 27: Genre listener profiles by annual personal income (USD)

Genre	≤$29,999	$30k-$49,999	$50k-$69,999	$70k-$89,999	$90k-$124,999	$125k-$199,999	≥$200k
Rock	-1	4	0	0	-1	1	-1
Pop	-3	1	0	1	0	2	-1
Country	5	1	-1	-1	-2	1	-2
Hip-Hop/Rap	4	3	-1	0	-1	0	-2
R&B/Soul/Funk	3	4	0	-1	0	-2	-2
Classical	-1	-5	0	2	1	0	3
Metal	3	3	-3	1	0	-3	1
Soundtracks	-2	0	0	2	1	1	-2
Indie/Alternative	2	-1	-3	1	0	3	-1
Jazz	-3	-4	1	1	6	0	1
Blues	1	0	6	0	-1	-2	0
Electronica/Dance	-4	1	2	1	-3	2	3
Folk	-4	-7	-2	-6	0	-4	3
MADs	3	3	1	1	1	2	2
% of deviations ≥ 5 pp	7						
% of deviations ≥ 10 pp	0						

Genres barely differ in their listeners' annual personal income (USD).

6.5. Genres listening does not differ by education

The composition of each genre's listening base, by minimum level of education completed, is compared in Table 28. Overall, it can be seen that genres attract a similar listener by the minimum level of education achieved. One larger difference was found for Metal listeners, who are 10 pp underrepresented holders of an Associate or Bachelor's College degree. Another larger difference occurs for high school graduates who are 9 pp underrepresented as listeners of Folk, compared to the average genre. Some consistent patterns are evident. For instance, Country and Hip-Hop/Rap listening is more prevalent among high school graduates and less among graduates of any university degree. Conversely, Classical listening is more prevalent among university degree holders and less prevalent among non-university degree holders. However, these listening patterns are marginal (≤7-pp) and do not demonstrate any compelling differences. Genres do not meaningfully attract a unique listener by minimum level of education completed. This is shown by the few differences greater than 5 pp (18%), 10 pp (2%) and low MADs ranging from 2-4 pp.

Table 28: Genre listener profiles by minimum level of education completed

Genre	High school graduate or less	Some college but no degree	Associate or Bachelor's Degree in College	Master's Degree	Doctoral or Professional Degree (e.g. JD, MD)
Rock	-1	3	1	-1	-1
Pop	-1	-1	4	0	-1
Country	6	3	-1	-4	-4
Hip-Hop/Rap	7	3	-4	-3	-3
R&B/Soul/Funk	3	5	-2	-2	-3
Classical	-4	-6	2	6	2
Metal	6	6	**-10**	-2	1
Soundtracks	0	-3	0	4	-1
Indie/Alternative	3	-1	2	-3	-1
Jazz	-7	-3	1	4	3
Blues	-7	1	5	0	1
Electronica/Dance	3	-3	-2	-1	3
Folk	-9	-3	4	3	4
MADs	4	3	3	3	2
% of deviations ≥ 5 pp			18		
% of deviations ≥ 10 pp			2		

Genres attract a similar type of educated listener.

6.6. Large similarity in genre listener employment status profiles

The composition of genres' listening bases are compared by current employment status in Table 29. While listeners of genres are mostly similar, some differences are evident. Country appeals 10 pp more to listeners who are full time homemakers, currently unemployed or retired than the average genre. Listeners of Folk are 10 pp less represented in the full-time employment status group. Country and Folk differences appear to reflect the differences also observed for age. One potential explanation is that older listeners (55+) are more likely to be retired.

Another larger difference is seen for listeners of Electronica/Dance, who are 11 pp underrepresented in the homemakers, currently unemployed or retired employment status group. This may also reflect age-related differences as 22 pp more 25-39-year olds listened to Electronica/Dance listeners. This young age group are unlikely to be full-time homemakers or retired. Overall, employment status listener characteristics differ minimally between genres, as 73% of deviations are below 5 pp and MADs are also low, ranging from 1-5 pp.

Table 29: Genre listener profiles by current employment status

Genre	Employed full time	Employed part time and/or College or High School Student	Full time housewife/husband, currently unemployed or retired	Self-employed or Other
Rock	-3	0	2	0
Pop	0	4	-1	-3
Country	-7	-4	**10**	1
Hip-Hop/Rap	5	3	-7	-1
R&B/Soul/Funk	4	-3	-1	0
Classical	-1	-3	4	-1
Metal	5	0	-4	0
Soundtracks	-7	3	4	1
Indie/Alternative	0	4	-6	2
Jazz	3	-6	-1	4
Blues	1	-5	4	1
Electronica/Dance	9	6	**-11**	-4
Folk	**-10**	1	7	2
MADs	4	3	5	1
% of deviations ≥ 5 pp	27			
% of deviations ≥ 10 pp	6			

Some genres attract different listeners by employment status, but the majority are small.

6.6.1. Listening device profiles

Table 30 compares each genre profile by listening device usage, for example, listeners of Rock who listen to music through CD, Radio, Spotify etc. Given that fewer older listeners use audio streaming (i.e. 44% of 55-64-year olds vs 83% of 16-24-year olds), and that genre listening differences by age are reported (International Federation of the Phonographic Industry 2019a), some listening devices differences might be expected. For example, more Classical listeners might listen to music on CD and radio than Hip-Hop/Rap listeners.

Some larger genre differences are found for devices used for music listening. In particular, listeners of Electronica/Dance listen to more music through their own iTunes library or pirated offline copies (14 pp) and YouTube (15 pp) than compared to the average genre's profile. Country music listeners use YouTube and other streaming services (12 and 10 pp respectively) less compared to the average genre's listeners. Other streaming services are also 10 pp less used by Rock's listeners. As 35% of deviations are 5 pp or more, the listening base of genres marginally differs by music listening device. However, only 3% of deviations are 10 pp or more and the MADs range from 3-5 pp, which shows that differences are not substantial. Genres are generally consumed through a number of different music listening devices of a similar proportion.

Table 30: Genre listener profiles by music listening device/ media type used for music consumption in the last week

Genre	CD	Radio	Vinyl or Cassette Tape	Portable Offline Music Device	iTunes Own Library or Pirated Music	Apple Music	Spotify (Paid)	Spotify (Free)	Pandora	YouTube	Other Streaming Service
Rock	-2	2	-7	-3	-5	-5	-6	-4	-6	-6	**-10**
Pop	-4	4	-6	-2	-2	-1	-3	-1	-2	-3	-7
Country	-4	9	-9	-4	-9	-4	-8	-4	-5	**-12**	**-10**
Hip-Hop/Rap	-9	-4	-5	-3	2	1	2	1	7	7	0
R&B/Soul/Funk	-7	-2	-3	-2	-7	-2	-5	3	3	4	2
Classical	7	2	0	-1	-2	2	0	-4	-2	-8	-2
Metal	2	-5	2	3	5	-1	0	2	-5	1	1
Soundtracks	4	-3	1	-1	6	4	1	-1	-2	0	5
Indie/Alternative	-4	-2	2	5	3	-5	4	6	0	3	4
Jazz	3	2	3	2	-1	3	5	-1	6	2	6
Blues	6	0	7	2	-1	1	2	-1	7	3	1
Electronica/Dance	-1	-4	5	4	**14**	7	6	6	6	**15**	9
Folk	9	-1	9	2	-3	1	1	-2	-7	-3	2
MADs	5	3	5	3	5	3	3	3	4	5	4
% of deviations ≥ 5 pp	35										
% of deviations ≥ 10 pp	3										

Some differences in music listening device are evident, but the majority are small.

6.7. Genre personality profiles

Links between personality and music preference are widely cited in the literature (e.g. Greenberg et al. 2016; Rentfrow & Gosling 2003). Therefore, genres were compared in their listening profiles using the Big Five personality traits as the key variable of investigation.

Table 31 compares the average raw personality trait scores for listeners of each genre to the raw average trait score. That is, for example, the difference between Rock listeners' average raw Openness personality score of (7.0) and the average Openness raw score of 6.9 (which includes listeners of any genre). Using this method of analysis, no differences of note were found. This is illustrated by the low MADs which range from 0.1 to 0.2 and the largest individual difference of 0.6.

Table 31: Genre listener profiles by average personality trait, when comparing the average genre raw score by trait to the mean raw overall trait score.

Genre	Openness	Conscientiousness	Extroversion	Agreeableness	Neuroticism
Average trait score	6.9	7.8	6.0	7.3	5.4
Rock	0.1	0.0	0.0	-0.1	0.1
Pop	0.1	-0.1	0.0	-0.1	0.3
Country	0.0	0.1	0.1	0.0	0.0
Hip-Hop/Rap	0.0	-0.4	0.2	0.1	0.3
R&B/Soul/Funk	0.2	-0.1	0.0	0.1	0.0
Classical	0.3	0.0	0.2	-0.1	-0.4
Metal	0.1	-0.5	0.0	-0.4	0.2
Soundtrack	0.2	0.0	0.1	0.1	0.1
Indie/Alternative	0.4	-0.4	-0.1	-0.5	0.2
Jazz	0.0	0.6	0.0	0.4	-0.3
Blues	0.3	0.0	0.3	0.0	-0.5
Electronica/Dance	0.4	-0.1	0.1	0.0	-0.5
Folk	0.0	-0.5	0.0	-0.4	0.3
MAD	0.1	0.2	0.1	0.2	0.2

No differences are found when comparing raw personality scores.

One potential explanation for such low deviations is likely due to the use of raw scale scores. Therefore, in line with other psychological research dealing with scales, raw scores were standardised (Fischer & Milfont 2010; Kim & Ferree Jr 1981). Personality trait scorers were then compared separately in three groups by the number of genre listeners that scored:

high (≥1 standard deviation), mid (≥-1 ≤ 1 standard deviation), and low (≤-1 standard deviation) for each personality trait.

Table 32 shows listeners classified as high in a Big Five personality trait (≥1 standard deviation). Larger differences are present using standardised scale scores than raw

scores. Of note, more respondents high in Openness listen to Folk compared to the average genre (9 pp). Another larger difference occurs for listeners high in Conscientiousness, who are less present in the listening base of Metal (-8 pp). Overall, 22% of deviations are 5 pp or more, which may indicate personality trait differences in the listeners of different genres. However, given that MADs range from 2-4 pp and no deviation is larger than 10 pp, any differences are negligible and unlikely to be actionable in practice.

Table 32: Genre listener profiles by big five personality trait for high scorers (≥1 standard deviation).

Genre	Openness	Conscientiousness	Extroversion	Agreeableness	Neuroticism
Rock	-2	2	1	-3	1
Pop	-2	0	2	-3	6
Country	-6	4	3	-2	-1
Hip-Hop/Rap	-5	-3	4	3	5
R&B/Soul/Funk	-1	2	-1	4	0
Classical	1	2	1	-3	-6
Metal	-4	-8	-6	—	-2
Soundtracks	0	3	3	2	2
Indie/Alternative	6	-3	0	—	-1
Jazz	4	5	-2	1	-6
Blues	6	3	-2	1	—
Electronica/Dance	-4	-6	-3	—	0
Folk	9	—	1	—	3
MADs	4	3	2	2	3
% of deviations ≥ 5 pp	22				
% of deviations ≥ 10 pp	0				

More differences are present among listeners high in a personality trait although none are large.

Genre profiles for low personality scorers, classified as scoring ≤-1 standard deviation, are shown Table 33. Some differences of note are found in the profiles of genres. Respondents low in Neuroticism are represented 10 pp more as listeners of Blues compared to the average genre. Blues therefore attracts fewer listeners who are high in Neuroticism. Another larger difference is found for listeners of Jazz, who are also low in Neuroticism (8 pp). Most other differences are small and between 0-3 pp. Only 18% of cases are 5 pp or more and only 2% are greater than 10 pp, with MADs ranging from 1-4 pp. Therefore, genres attract a similar proportion of low personality trait scorers.

Table 33: Genre listener profiles by big five personality trait for low scorers (≤1standard deviation)

Genre	Openness	Conscientiousness	Extroversion	Agreeableness	Neuroticism
Rock	1	-4	1	-1	-1
Pop	0	-3	3	0	-6
Country	0	-6	3	-2	-1
Hip-Hop/Rap	-1	4	-2	-2	-5
R&B/Soul/Funk	0	0	0	-1	0
Classical	-2	-4	0	0	5
Metal	-1	6	-2	3	-4
Soundtrack	0	-5	1	-3	-2
Indie/Alternative	-1	3	2	4	-3
Jazz	3	0	—	-1	8
Blues	1	-2	-5	-2	**10**
Electronica/Dance	-1	5	-1	4	—
Folk	—	6	—	4	-1
MADs	1	4	2	2	4
% of deviations ≥ 5 pp			18		
% of deviations ≥ 10 pp			2		

One large difference is observed, but the remainder are negligible for listeners low in personality traits.

The profiles for respondents who score moderately in personality trait (≥-1&≤1 standard deviation) are compared in Table 34. More differences greater or equal to 5 pp were found in this analysis (26% deviations ≥ 5 pp) than for respondents high and low in a personality trait. Notable differences occur for respondents moderate in Extroversion, who are overrepresented in the listening bases of Metal (8 pp) and Jazz (9 pp) compared to the average genre. Some other larger differences occur for respondents moderate in Openness, who are underrepresented as listeners of Jazz (-8 pp) and Blues (-8 pp) compared to the average genre. Overall, no deviations are 10 pp or larger indicating similarity between genres in listeners moderate in personality traits.

Table 34: Genre Listener profiles by Big Five personality trait for mid scorers (≥-1 & ≤ 1 standard deviation)

Genre	Openness	Conscientiousness	Extroversion	Agreeableness	Neuroticism
Rock	1	2	-3	2	-1
Pop	2	3	-6	2	-1
Country	5	2	-8	2	1
Hip-Hop/Rap	6	-2	-3	-2	-2
R&B/Soul/Funk	1	-2	1	-4	-1
Classical	0	1	-2	2	0
Metal	5	2	8	2	5
Soundtrack	-1	2	-5	-1	-1
Indie/Alternative	-5	0	-2	0	3
Jazz	-8	-5	9	-2	-4
Blues	-8	-2	6	-1	-5
Electronica/Dance	5	0	4	-3	8
Folk	-3	-1	-1	2	-3
MADs	4	2	4	2	3
% of deviations ≥ 5 pp			26		
% of deviations ≥ 10 pp			0		

Genres differ little in listeners who are moderate in personality.

A summary of deviations for personality trait analyses is shown in Table 35. Overall, more than 78% of personality deviations were less than 5 pp, which demonstrates that any personality differences in genre listening are negligible.

Table 35: Deviation summary for personality trait analyses

Analysis Type	% of Deviations ≥5 pp	% of Deviations ≥ 10 pp	Average Deviation
Trait Average	0	0	0
High	22	0	3
Mid	26	0	3
Low	18	2	3
% of all deviations	22	1	3
Average Overall MAD		2	

Personality differences between genres are negligible.

6.7.1. Hedonic and eudaimonic motivations for listening

Table 37, compares genres' listening bases for the average standardised scores for listeners high (≥1 standard deviation), moderate (≥-1 & ≤1 standard deviation) and low (≤-1 standard deviation) in hedonic and eudaimonic music listening motivations. While all genres do not meaningfully differ in their listener's motivations, there are some differences of note. Specifically, Country listeners are less likely to be high in eudaimonic listening motivations (-7 pp), while the reverse occurs for Jazz listeners (7 pp). On the other hand, Country listeners are slightly more moderate in their eudaimonic motivations (5 pp). Again, the reverse occurs for Jazz (-6 pp). The only other difference of note is observed for Soundtracks, where its listeners are neither high or low in hedonic motivations (-5 pp).

Despite some slight differences, no genre is significantly unique in their listeners eudaimonic or hedonic music listening motivations. This is demonstrated by the small MADs of 2-3 pp and the absence of large deviations (≥10 pp). Further, 88% of these deviations are less than 5 pp, which shows the large similarity between genres.

Table 36: Summary of overall MADs for genre listener profiles by hedonic and eudaimonic motivations

Analysis Type	% of deviation ≥ 5 pp	% of deviations ≥ 10 pp	Average MAD
High	12	0	3
Mid	8	0	2
Low	4	0	2
ALL	12	0	
Average Overall MAD		2	

Motivations for music listening differ little between genres.

Table 37: Motivation profiles for high scorers (≥ standard deviation)

Genre	Eudaimonic Motivations			Hedonic Motivations		
	Low	Mid	High	Low	Mid	High
Rock	3	1	-4	1	-1	1
Pop	1	2	-3	-2	0	-2
Country	2	5	-7	1	-1	1
Hip-Hop/Rap	-1	1	-1	1	-3	1
R&B/Soul/Funk	-2	0	2	1	-2	1
Classical	2	-2	0	4	-4	4
Metal	2	0	-3	4	-1	4
Soundtracks	-2	3	-1	-5	2	-5
Indie/Alternative	1	-2	1	2	3	2
Jazz	-1	-6	7	-3	4	-3
Blues	-3	-1	4	-1	2	-1
Electronica/Dance	-2	1	2	-3	-2	-3
Folk	-1	-2	4	1	3	1
MADs	2	2	3	2	2	2
% of deviations ≥ 5 pp	12					
% of deviations ≥ 10 pp	0					

Genres are similar in their listeners' eudaimonic and hedonic motivations for music listening.

6.8. Genres differ little in their demographic and psychographic listener profiles

Study Two investigates the extent that genres are similar in their demographic, psychographic and music media usage listener profiles through two research questions:

RQ2a: Do music genre listener-profiles differ by demographic or usage variables?

RQ2b: Do music genre listener-profiles differ by psychographic variables?

Overall, more differences were found for gender and age variables, with around 3 quarters of all gender deviations (77%) and half for all age deviations (56%) greater or equal to 5 pp (a summary of deviations is shown in Table 38). However, less than a quarter of all gender and age cases were greater or equal to 10 pp and therefore most differences were small. Gender and age MADs (6-7 pp) were on average larger than other variables, although the MADs are still quite low in consideration of differences claimed in prior studies (e.g. Greenberg et al. 2016; Rentfrow & Gosling 2003). Similarly, 35% of music media usage profiles exceeded 5 pp or more, but few exceeded 10 pp. Some

differences may therefore be present in music media usage, but these differences are predominantly small and therefore difficult to identify on aggregate. Personality and motivation psychographic variables differed the least of all variables, with only 15% of all psychographic cases greater or equal to 5 pp. Differences were more pronounced for gender and age variables, which is consistent with music and radio studies (e.g. North 2010; Winchester & Lees 2013). Some genres may therefore attract a slightly different type of listener by gender and age. With the exception of gender and age, the majority of deviations are less than 5 pp, which is small and unimportant (Barwise & Ehrenberg 1988). Only 12% of demographic and <1% of psychographic cases reach 10 pp, which shows that genres are largely more similar than different in their listener profiles.

Table 38: Summary of deviations for demographic, music media usage and psychographic variables

Variable	% of deviations ≥ 5 pp	% of deviations ≥ 10 pp	Average MAD
Gender	77	23	7
Age	56	23	6
Ethnicity	29	15	5
Annual Personal Income	7	0	2
Minimum Education Level	18	2	3
Employment Status	27	6	3
ALL DEMOGRAPHICS	39	12	3
Music Media Usage	35	3	4
Personality Trait	16	<1	2
Motivations	12	0	2
ALL PSYCHOGRAPHICS	14	<1	2

Gender and age account for the most difference in genre listening.

7. Study Three Method

7.1. A replication to understand the age at which musical preferences develop

Holbrook and Schindler's (1989) and Hemming's (2013) research explores the age at which individuals develop their popular musical preferences. The initial finding was that preferences for popular music are formed during late adolescence or early adulthood, at approximately 23 years of age (Holbrook & Schindler 1989). Therefore, popular music preferences may be influenced by nostalgia. Due to the larger age listening differences between genres in Study Two, especially among older aged listeners, this analysis replicates Holbrook and Schindler's (1989) original study to provide additional clarity.

7.1.1. Research design and task

Data comes from the same 1,036 US nationally representative sample as mentioned in 5.2. For the final task in the survey, respondents were exposed to 30-second excerpts of 34 selected songs. Respondents were exposed to the 34 songs in an individually randomised order. The songs come from the Billboard top 10 charts from 1950 to 2016 selected at random in two-year intervals. All top three Billboard chart songs were excluded to avoid the effect of potential outliers. Each selected song is intended to be representative of its respective year. A full list of the 34 songs appear in Table 40. All 30-second excerpts were carefully trimmed so that the essence of the song was captured i.e. part of the chorus and verse. Preference for each song was assessed on a 10-point Likert scale ranging from 0 ("I dislike it a lot") to 10 ("I like it a lot"), as in the original study (Holbrook & Schindler 1989). The scale also includes a neutral point at 5 ("neither like or dislike"). To ensure that respondents listened to a reasonable portion of each excerpt, a minimum of 10-seconds of each song had to be consumed. Respondents could advance to the next song from the 11th second.

7.1.2. Analysing a peak in popular music preferences

First, the age of the respondent and the year that each song featured in the Billboard top 10 charts form a song-specific age (SSA) for each respondent and song. This independent variable is the age of the respondent at the time that each song became a hit. For example, if a respondent was born in 1964, their SSA for the song representing 1988 is 24. On the other hand, a negative SSA means that the song was featured in the Billboard Top 10 prior to that respondent's birth. For example, an SSA of -24 for a respondent born in 2000 means they were born 24 years after that song featured in the Billboard Top 10. Therefore, if Holbrook and Schindler's (1989) finding that preferences for popular music peaks during late adolescence or early adulthood holds true, the SSA associated with the maximum preference in this research should be between the high teens or low twenties.

The present SSA calculation provided a range of 133 (from -51 to +81), each consisting of different songs for differently aged respondents. SSAs are recoded

as a deviation from their own mean in order to minimise collinearity, as in Holbrook and Schindler's (1989) and Hemming's (2013) studies. To account for differences in how individuals might use the rating scale, or enjoy popular music overall, individual ratings are standardised by subtracting the mean of the individual's ratings and dividing by the standard deviation. These standardised ratings are then aggregated by SSA, and the mean for each SSA is calculated to provide the dependent variable (standardised musical preference). These variables are then analysed through models of multiple regression. Generation and gender cohorts are also analysed separately. These generations are defined by the Pew Research Centre (2019). The generation definitions are shown below in Table 39.

Table 39: Generations as defined by the Pew Research Centre (2019).

Generation	Born	Age in 2019
Silent	1928-45	74-91
Boomers	1946-64	55-73
X	1965-80	39-54
Millennials	1981-96	23-38
Z	1997-2012	7-22 (ongoing)

Table 40: Songs and their respective Billboard top 10 year, used as stimuli in US Consumer Survey

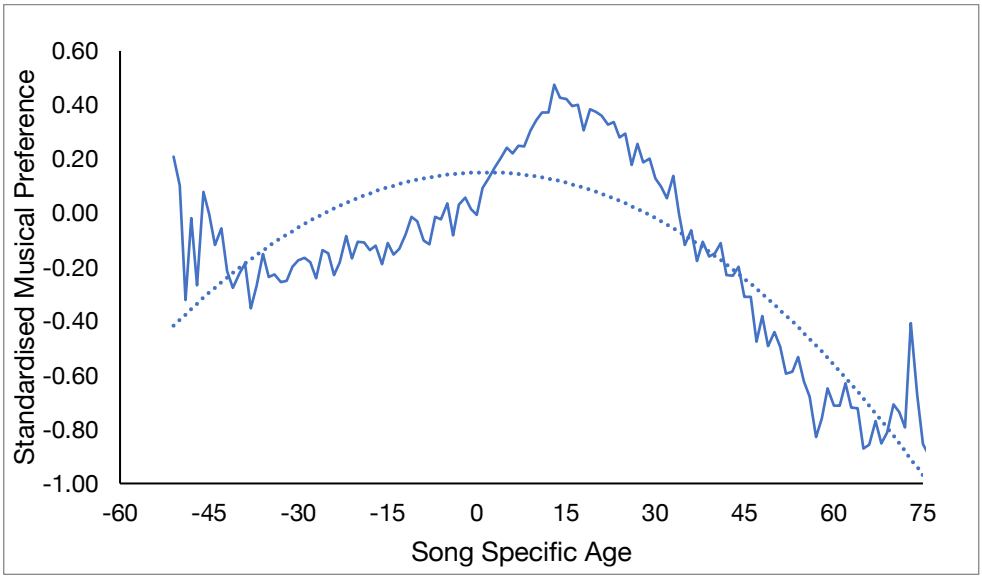
Song Year	Song Title	Performer/s
1950	Play a Simple Melody	Bing and Gary Crosby
1952	You Belong to Me	Jo Stafford
1954	Sh Boom Sh Boom	The Crew Cuts
1956	My Prayer	The Platters
1958	Patricia	Perez Prado
1960	Running Bear	Johnny Preston
1962	Roses are Red	Bobby Vinton
1964	I Get Around	Beach Boys
1966	The Last Train to Clarksville	The Monkees
1968	People Got to be Free	The Rascals
1970	Raindrops Keep Fallin' on My Head	B.J. Thomas
1972	Lean on Me	Bill Withers
1974	The Sound of Philadelphia	MFSB ft. Three Degrees
1976	Play that Funky Music	Wild Cherry
1978	Stayin' Alive	Bee Gees
1980	Crazy Little Thing Called Love	Queen
1982	Don't You Want Me	Human League
1984	Footloose	Kenny Loggins
1986	Party All the Time	Eddie Murphy
1988	Sweet Child O' Mine	Guns N' Roses
1990	Vogue	Madonna
1992	Under the Bridge	Red Hot Chilli Peppers
1994	All She Wants	Ace of Base
1996	Missing	Everything but the Girl
1998	Crush	Jennifer Paige
2000	Say My Name	Destiny's Child
2002	Dilemma	Nelly ft. Kelly Rowland
2004	Hey Ya	OutKast
2006	Sexy Back	Justin Timberlake
2008	Lollipop	Lil Wayne
2010	California Gurls	Katy Perry
2012	Payphone	Maroon 5
2014	Counting Stars	One Republic
2016	Work	Rihanna

8. Study Three Results

8.1. Do popular music preferences peak during late adolescence or early adulthood?

As shown in Figure 2, a peak in popular music preferences is observable. However, the relationship between song specific age (SSA) and mean standardised preference is not perfectly an inverted U-shape as in the original study (Holbrook & Schindler 1989). Multiple regression analysis reveals a significant relationship between popular musical preferences and Song Specific Age (SSA) ($R^2 = 0.73$, $F(2, 130) = 179.6$, $p < 0.001$). This is significant for both Song Specific Age ($t(130) = -11.8$, $p < 0.001$) and Song Specific Age squared ($t(130) = -14.9$, $p < 0.001$). When the data is fitted with a quadratic term (shown in Figure 2), the age peak in popular musical preference is estimated by setting the first derivative of the regression equation equal to zero. Note that SSA was recoded as a deviation from its own mean to minimise multicollinearity between SSA and $SSA^{2,}$ as performed by Holbrook and Schindler (1989) and Hemming (2013). The figure derived from calculus is -13.6, which is translated into an actual age by re-adding the mean of 15 (since SSA is recoded as a deviation from its own mean). This provides an age of 1.4 when maximum music preference is attached.

Figure 2: Relationship between song specific age and musical preference



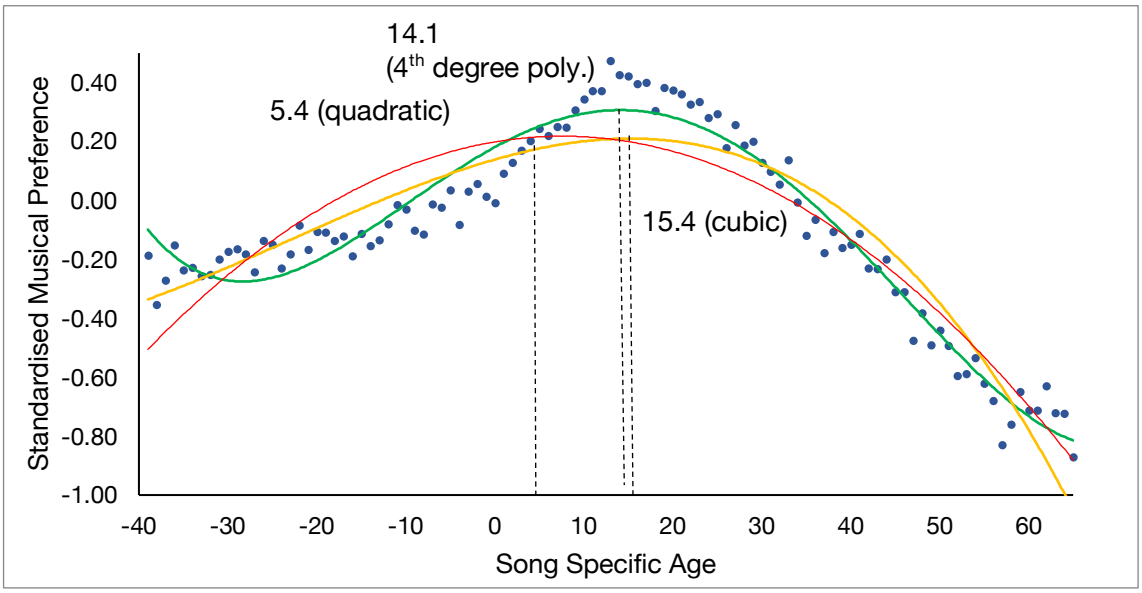
Preference = -0.000207*SSA2-0.005633*SSA+0.113

The age of 1.4 is a radical departure from Holbrook and Schindler's age of 23.5 (Holbrook & Schindler). Upon graphical inspection, the model fits poorly towards the peak of the data, which is the area of particular interest. In the present data, the fit of the quadratic term is also affected by the tails occurring for the low and high SSAs. The age peak of 1.4 is appears to be an artefact of the data, as the maximum point of the observed values does not coincide with that of the quadratic term. As such, it is unsuitable to draw any inference from this particular analysis. Therefore, unreliable observations or

outliers are removed to improve the stability and validity of results, as suggested by Holbrook and Schindler (2013).

The data was trimmed to include SSAs consisting of 100 or more individual ratings. For example, since each SSA is aggregated and the mean standardised preference for each SSA is calculated, fluctuation occurs in the number of individual ratings due to absolute differences in respondent's age. Low numbers of ratings typically occur at the extreme low and high SSAs. Consequently, trimming the data leaves 105 SSAs ranging from -39 to 65. Holbrook and Schindler (2013) are critical of Hemming's (2013) arbitrary cut-off at N ≥50 for SSAs, which left 78 SSAs ranging from -28 to 49. Holbrook and Schindler (2013) analysed an SSA range of 118, which is only 13 more than this analysis. Therefore, the SSA range is deemed adequate for further analysis.

Figure 3: Quadratic, cubic and fourth-degree polynomial relationship between Song Specific Age and musical preference



Multiple regression analysis reveals a strong relationship between SSA (consisting of a quadratic term) and music preference (R^2 = 0.82, F (2, 102) = 238.7, $p < 0.001$). However, after setting the first derivative of the quadratic equation equal to zero, musical preferences peak at 5.4 years of age. This is still drastically lower than Holbrook and Schindler's (1989) age of 23.5. Again, the issue appears to be that the quadratic term fits poorly towards the actual peak of the data (see Figure 3). One alternative to fit a cubic equation to the data, which was suggested by Holbrook and Schindler (2013) to Hemming (2013). The statistical fit of the model was improved by the cubic term (R^2 = 0.87, F (3, 101) = 220.2, $p < 0.001$). The preference peak associated with the cubic equation increased to 15.4 years of age. However, the fit of the cubic was also poor towards the peak of the observed values. Further modelling of a fourth-degree polynomial equation increased the strength of the statistical fit (R^2 = 0.94, F (4, 100) = 380.48, $p < 0.001$). The age attached to a peak in popular musical preferences, based on the fourth-degree polynomial model, is 14.1, a slight age

decrease from the cubic model. Therefore, popular music preferences peak when and individual is between 14 and 15.5 years of age (see Figure 3).

8.1.1. Popular music preferences peak during early to mid-adolescence

These findings provide broad support for the seminal study (Holbrook & Schindler 1989) but also counter evidence to the German sample replication (Hemming 2013). Based on this analysis of US music listeners, popular music preferences still peak during adolescence. However, preferences for popular music do not peak during late adolescence or early adulthood. Based on the present analysis, a more apt proposition is that preferences for popular music peak during early to mid-adolescence. This is demonstrated through a number of analyses, which finds a peak occurring between 14 and 15.5 years of age.

While calculus finds a peak by graphical inspection, the relationship between popular music preferences and age is more plateaued. That is, maximum music preference is not as high as the prior studies. Therefore, the age at which preferences for popular music peaks is not precise. Rather, maximum popular music preference approximately occurs between the ages of 14 and 15.5. The finding that preferences for popular music peaks at around 14-15.5 years of age, is almost 10 years younger than the age of 23.5 found in Holbrook and Schindler's study (1989). This might reflect the increased availability of music over time. For instance, older individuals had much lower access to music during their adolescence compared to the current online streaming accessibility afforded to everyone today. Therefore, younger generations may have an increased exposure to music at a younger age. This is also acknowledged by Hemming (2013) as a potential cause for a decline in nostalgia. One other explanation is that this analysis was conducted on a different cohort of listeners, that is, on groups of people who may be more or less nostalgic, and therefore display a lesser affection to the songs released during their late adolescence or early adulthood. To investigate this possibility, differences in this peak between groups in the sample are explored. Specifically, the different generational cohorts.

8.1.2. Generational effect on popular music preferences are evident

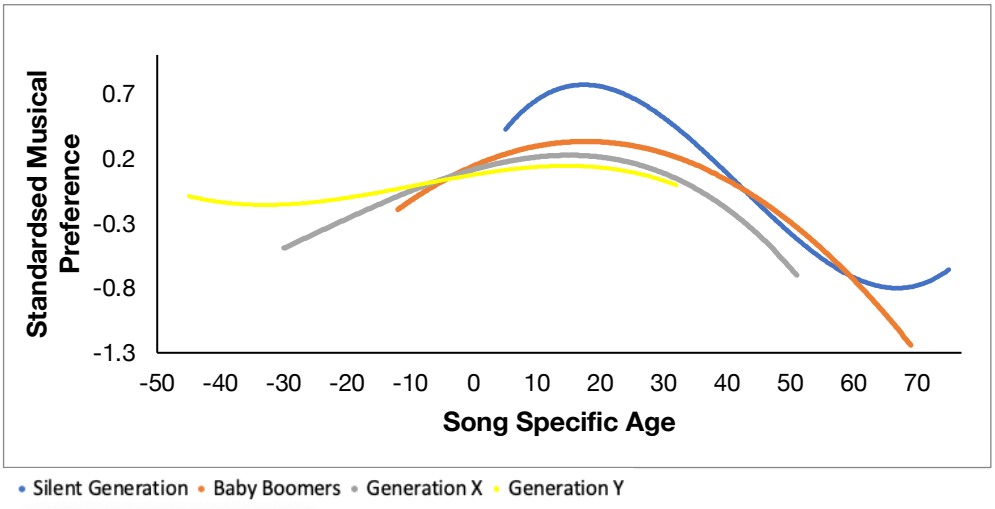
Generational cohorts are examined in order to determine whether differences in maximum musical preference are the result of generational cohort. The five generations are defined by the Pew Research Centre (2019). As the number of individual ratings that formed the aggregated SSA is much lower than the full sample (ratings only included respondents from one generational cohort), only SSAs consisting of 20 or fewer ratings are removed. Each generation consists of different ranges of SSAs, due to absolute differences in age. For example, Silent Generation SSAs are no lower than 5 and as high as 75. Conversely, Gen Z SSAs are as low -50 and no higher than 19. Each

generational cohort analysis is therefore fitted with the most suitable regression model. Sampling statistics for each generational cohort are displayed below in Table 41.

Table 41: Sampling statistics for generation cohorts

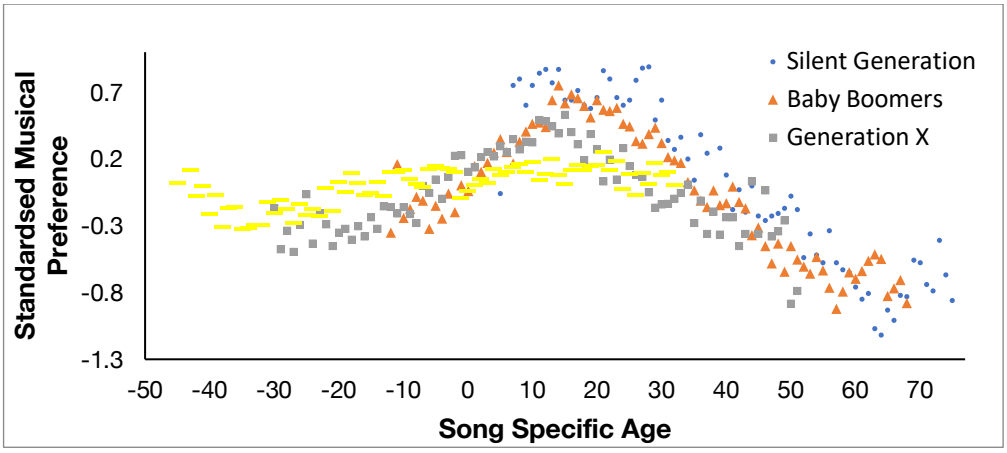
Generation	Number of respondents in generation	SSA (min & max)	SSAs excluded	Size of SSA range
Silent (1945 or before)	85	5 to 75	6	70
Baby Boomers (1946 to 1964)	307	-12 to 69	-14,-13,70	82
X (1965 to 1980)	288	-30 to 51	—	81
Y (1981 to 1995)	279	-45 to 32	33,34,35	77
Z (1996 ongoing)	77	-50 to 19	-51,19	70

Figure 4: Visualisation of the relationship between musical preference and SSA by generational cohort



*Silent generation preference = 0.000026*SSA^3 – 0.0001664*SSA^2 -0.047318*SSA + 0.085*
*Baby Boomers preference = 0.000013*SSA^3 – 0.000597*SSA^2 -0.026156*SSA + 0.261799*
*Generation X preference = 0.00000044944*SSA^4– 0.000004*SSA^3 - 0.001137*SSA^2 + 0.003997*SSA + 0.3219*
*Generation Y preference = -0.000006*SSA^3– 0.000054*SSA^2+0.00928*SSA + 0.02201*

Figure 5: Spread of musical preference by generational cohort



A visualisation of the relationship between standardised musical preference and SSA for all generational cohorts (excluding generation Z) is shown in Figure 4 and Figure 5. Each generational cohort displays some age peak for popular music preferences (see Table 42). It is evident that the age at which popular music preferences peak, generally declines from oldest to youngest generation. That is, as the oldest cohort, respondents in the Silent generation display a higher preference for music that was popular during their adolescent years, than the generation Y, the youngest cohort (see Figure 4 and Figure 5). The most notable difference in the age that popular musical preferences peak occurs between the Silent generation and Baby Boomer generational cohorts. As the oldest cohort, the Silent generation peaks in popular music preference at around 18 years of age, while baby boomers are 14 and generation X and Y listeners are 13-14. This may reflect the vast inequities between these two generations in the availability of music during their adolescence. As a whole, this analysis shows that the age that popular music preferences peak, decline through generational cohorts, which may explain the more plateaued preference peak in the full sample analysis (See Figure 2 and Figure 3). That is, the effect of nostalgia, may be declining among younger generational listeners. See Table 42 for the regression results. There is also the possibility that, as each of these generations age, the effect of nostalgia will become more powerful for them, and their preferences for music may change.

Note that the Generation Z cohort did not display a sufficient statistical fit in the regression model ($R^2 = 0.25$). This may because this group could not obtain an SSA of less than 20 and therefore had a much smaller sample size. Therefore, the full regression analysis was not performed on this cohort.

Table 42: Key regression descriptives for each generational cohort

	Silent	Baby Boomers	Generation X	Generation Y
Regression	$F(3,66) = 294$, $p < .001$	$F(3,78) = 188.4$, $p < .001$	$F(4,76) = 76$, $p < .001$	$F(3,73) = 36.4$, $P < .001$
R^2	.93	.88	.80	.60
Age Peak	17.9	13.7	12.7	13.9

The age that preferences for popular music peaks broadly declines from oldest to youngest generational cohort.

9. Discussion, Contributions, Limitations and Future Research

9.1. Music listening follows the law of DoP

The law of Duplication of Purchase (DoP) states that the level of customer sharing between any pair of brands can be predicted by the size of the two brands (Goodhardt & Ehrenberg 1969). Specifically, a brand shares many of its customers with larger brands and far fewer with smaller brands. Study One of this thesis addresses the research questions:

RQ1a: Does music listening follow the law of Duplication of Purchase for (a) genre, (b) album, (c) artist, and (d) songs?

RQ1b: Is there evidence of any partitioning between genres?

Music listening closely follows the law of DoP for genres, artists, albums and songs. This is demonstrated by observing the broad pattern whereby two music brands share in line with size, across 21 large sets of data of 1-year music listening, in addition to 4 sets of data for 6-month, 3-month, monthly, and 1-week time periods. Additionally, tests of fit measures demonstrate the similarity between the observed and expected sharing levels outlined by the law of DoP.

This finding is summarised as:

The level of listener duplication between two genres, artists, albums or songs will vary according to the penetrations of both brands, in line with the law of Duplication of Purchase and Viewing.

9.2. Support for DoP research

The finding that the law of DoP describes music competition, supports earlier DoP research in media (Goodhardt & Ehrenberg 1969; Lees & Wright 2013), entertainment (Lam & Ozorio 2013), tourism (Dawes et al. 2009) and consumer packaged goods contexts (Bass 1974). Study One findings are consistent with radio station listening research (Lees & Wright 2013). However, where Lees and Wright (2013) found evidence of partitioning by format between talk and music stations, no evidence of partitioning of music genres is found. Replication and extension are required in order to confirm this is entirely the case. In particular, examination of artists, albums and songs is needed to corroborate a lack of market partitioning.

While sub-genres overshare listeners with another sub-genre that belongs to the same meta genre (e.g. Soft Rock and J-Rock grouped as Rock), they are not partitioned from the market and share as expected with any other genre. For example, Trance and House (aggregated as Electronica/Dance) may overshare listeners with each other but share as expected with all other genres. Even the genre partitions tested (e.g. Classical versus Electronica/Dance) do not under-share listeners. This means that listeners of a genre such as Electronica/Dance do not completely avoid a musically different genre such as Classical. The

overall pattern is that the likelihood of listening to any pair of genres, artists, albums or songs, can be estimated by the size of the overall listener base. These findings are therefore consistent with DoP television audience research where the size of the audience is the main determinant of duplication (Ehrenberg & Goodhardt 1969; Goodhardt 1966; Goodhardt & Ehrenberg 1969). However, where the prior DoP/DoV research found an average MAD of 1, in this research, a slightly higher a MAD of 3 is found. This may be due to the many more brands in the music market and therefore greater variability in sharing.

9.3. Genre listener profiles are demographically and psychographically similar

Empirical marketing research finds that competing brands rarely attract a unique type of demographic or psychographic customer (e.g. Hammond et al. 1996; Uncles et al. 2012). The current research analysed the listener profiles of 13 genres using a nationally representative sample of the USA (n=1036), to determine whether the same is true for music genres.

Study Two of this thesis investigates the research questions:

RQ2a: Do music genre listener-profiles differ by demographic or usage variables?

RQ2b: Do music genre listener-profiles differ by psychographic variables?

Genres are found to be similar in their demographic and psychographic listener profiles. In consideration of a managerially significant difference in genre listener profiles; that is, a difference in the profiles that is actionable, few instances are found where a genre attracts a unique demographic or psychographic listener.

9.4. Genre listening differs the most by age

The largest differences in the listening bases of different genres are observed for age. Around a quarter of age deviations exceed the 10-percentage point level of managerial significance. The majority of these ± 10 deviations occur among listeners aged 55 or older with the remainder occurring among 25-39-year-olds. Specifically, 55+ year-olds are underrepresented in the listening bases of Hip-Hop/Rap and Electronica/Dance compared to other genres (≤-10 pp). On the other hand, this age group is overrepresented as listeners of Country, Classical, Jazz, Folk and Blues (≥ 10 pp). This is consistent with North's (2007c) research where an older demographic listened to Classical and Country. Excluding listeners aged 55+, most other age differences are negligible. There is more variation in age than other demographic variables given that almost three quarters of deviations are 5 pp or more. The finding that genre listening varies most by age is consistent with studies where age explained the most variance in musical preference (North & Hargreaves 2007c; North 2010; Savage 2006).

9.5. Popular music preferences are affected by nostalgia

Given the importance of age in the different genre listener profiles, the effect of nostalgia on popular music preferences is also explored. This thesis confirms previous findings (i.e. Holbrook & Schindler 1989) that preferences towards popular music peak during a period of adolescence. Preferences for popular music were found to peak during early to mid-adolescence when an individual is around 14-15.5 years old.

While, calculus finds an age peak in preferences for popular music, by graphic inspection, the relationship between popular music preferences and age appears more plateaued. Therefore, there is not a precise age that popular music peaks. Rather, there is an approximate range, which is between 14-15.5 in the present research. Graphical inspection does reveal that the nostalgia effect is weak before the age of zero, and that before birth, actual preference controls the rating for a specific song. However, as soon as age is greater than zero, a nostalgia effect becomes clear.

The finding that preferences for popular music peak when an individual is between 14 and 15.5 years of age, differs from Holbrook and Schindler's (1989) original age of 23.5 by nearly a decade. Hemming (2013) was the first to replicate the seminal paper and reports an age of 8.6, which conflicts with findings in the present research. Hemming (2013) explained the decrease in age for maximum popular musical preference by increasing media familiarity and exposure to music at a younger age, which might also be the case for the current research. Such an explanation seems to have face validity, especially when considering the significantly easier access to music due to the rise of music streaming. Separate analysis by generation finds that there is a decreasing age peak over generation from around 18 (silent generation born 1945 or before) to 14 (Y generation born 1981-1996). This provides an explanation as to why an overall lowering in age peak is observed.

Nostalgia may also provide an explanation as to why the largest differences are found in the age groups of the listeners of different genres. These age deviations may be a result of a music genres popularity (or lack of) during an individual's teen/adolescence years, especially among listeners aged 55+ where 70% of deviations are notable (≥10 pp). However, further research into the effect of age and nostalgia on music listening is required to confirm this proposition. Future research should also examine a wider variety of music beyond popular music and explore why a nostalgia effect occurs for musical preference.

9.6. Contributions to theory

9.6.1. Replications and extension of empirical generalisations

Given the importance of replications in building knowledge, this thesis conducts two replication studies. Two empirical generalisations (EG) are applied to music listening behaviour through a differentiated replication design (Lindsay & Ehrenberg 1993). An EG is characterised by observation across a range of conditions where the same lawlike pattern recurs in spite of differing research environments (Bass 1995; Uncles & Wright 2004).

The first EG is the law of Duplication of Purchase (DoP), which is that customer sharing between any pair of brands is predictable and driven by the size of the brands (Goodhardt & Ehrenberg 1969). The Law has been found to describe brand competition in contexts as diverse as consumer packaged goods (Bass 1974), industrial buying (Ehrenberg 1975), cars (Bennett & Graham 2010), leisure and entertainment (Lam & Ozorio 2013) and radio listening (Lees & Wright 2013). This research demonstrates the application of the Law to music listening behaviour in a digital and streaming environment, an unexplored context.

The second EG is that the user profiles of directly competing brands seldom differs (Hammond et al. 1996). This means that competing brands do not attract a unique demographic or psychographic type of customer. Substituting brands for music genres, this thesis finds that listeners of different genres are more similar than different in terms of their demographic and psychographic variables. This supports findings in luxury goods (Patrick et al. 2016), high street fashion (Bennett et al. 2016), retailers (Kennedy & Ehrenberg 2001a), fresh produce (Anesbury et al. 2018a) and media such as radio station listening (Nelson-Field et al. 2011).

Results confirm that the law of DoP holds for music listening and that genres attract very similar demographic and psychographic listeners. This research contributes to the wide body of empirical marketing research by extending the generalisability of these EGs to a music context and demonstrating that music, at least at the genre level, is not a boundary condition.

9.6.2. Findings counter to the music literature

9.6.2.1. Music literature finds demographic and psychographic differences

This research finds conflicting evidence to that previously reported in the music literature. Studies in the music field report that genres have different listener profiles by demographic variables such as age, gender, race,

occupation, education, employment, income and so on (e.g. North 2010; van Eijck 2001). For example, Rock is listened to by white, male, young and middle social class listeners, while Jazz is listened to by urban professionals and managers (Savage 2006). Psychographic differences, in particular, personality, are also reported as a means of profiling fans of genres (e.g. Greenberg et al. 2016; Rawlings & Ciancarelli 1997). As an example, intense and rebellious genres (Alternative, Rock and Heavy Metal) are positively related to the Openness personality trait and therefore knowledge of an individual's music preferences could serve as a cue for their personality (Rentfrow & Gosling 2003).

9.6.2.2. Marketing analysis finds no demographic or psychographic differences

Music research findings suggest that demographic and psychographic variables could serve as means for identifying individual music preferences. This is at odds with empirical marketing knowledge, where the buyers of competing brands are rarely different in demographic, psychographic and media usage variables (e.g. Anesbury et al. 2017; Uncles et al. 2012). Few notable demographic and psychographic differences in the listener profiles of genres are found in this research. Genres rarely attract a unique demographic or psychographic music listener, which suggests that music listening behaviour may follow additional empirical patterns observed in consumer behaviours such soft drink purchasing.

9.6.2.3. Prior differences may have been overstated

Studies in the music field typically place a large emphasis on statistical significance (e.g. Rawlings & Ciancarelli 1997; Rentfrow & Gosling 2003). This contrasts with the analysis method used in Study Two of this thesis, for genre listener profiles. Study Two uses Hammond and colleagues' (1996) analysis method to compare each genre's profile to the average of all genres, that is, the category profile. This analysis method has been widely used in brand user-profile research (Kennedy & Ehrenberg 2001a, 2001b; Uncles et al. 2012). Hammond et al.'s (1996) analysis approach focuses only differences of managerial relevance rather than statistical significance. Managerial relevance refers to brand profile differences that are meaningful to marketing practitioners as they are strategically actionable (Kennedy et al. 2014).

The finding that genre listener profiles are more similar than different across demographic and psychographic variables, suggests that differences reported in the music literature may have been overstated. For example, correlations between personality and music preference are generally $r < .30$, which are relatively weak (e.g. Delsing et al. 2008; George et al. 2007; Rentfrow & Gosling 2003; Zweigenhaft 2008). Yet, these correlations are reported as strong indications of the link between personality and music preference. Personality is also reported to predict music preference far beyond demographic variables (e.g. Greenberg et al. 2016). The results of this thesis suggest that the link

between personality, demographics, and music listening is not as strong as some studies propose (i.e. psychographics overall MAD = 2). However, more and larger notable differences were found for age (quarter of all age deviations ≥ 10 pp). Therefore, findings are supportive of North's findings (2010) that demographics, especially age, is more related to music listening than psychographics.

This thesis does not propose that individual demographic and psychographic differences in music preferences do not exist at all or that weak correlations are not meaningful. It is however asserted that a managerially significant (rather than a statistically significant) interpretation of results and avoiding preconceptions that differences should exist, leads to fewer and smaller differences than previously suggested. When using an aggregate perspective, such differences are harder to detect and ensure as a marketer. As such, the findings in this thesis may reflect the different methods and aims and interests between the fields of marketing and psychology, where many music studies originate from (e.g. Greenberg et al. 2016; Rawlings & Ciancarelli 1997). Specifically, this thesis adopts the empirical generalisation philosophy popularised by Andrew Ehrenberg and colleagues (Barwise 1995; Ehrenberg 1966, 1995). Consequently, the emphasis is on generalisable results that are established through replication, many sets of data and significant sameness (Ehrenberg 1990; Kennedy et al. 2014).

9.7. Contributions to practice

9.7.1. Popular artists are your main competitors

Competition between genres, artists, albums and songs is driven by brand size. This finding provides benchmarks for brand growth and an understanding of where sales (or listens) are likely to be gained or lost (Dawes et al. 2009). Therefore, an artist should expect to share most of their listeners with larger artists and far fewer with smaller artists. That brand size is the main determinant for listener sharing shifts the focus away from similarly positioned brands towards competition with the large music brands (Dawes 2008). These large dominant brands are where listeners are most likely to be lost and gained.

9.7.2. Focus on all listeners, not just the 1,000 true fans

The finding that penetration drives brand competition in music provides realistic brand growth strategies. With most listeners also listening to the large music brands, future listens are more likely to come from category listeners, rather than repeat listeners (Bennett 2008). The application of the law of DoP to music listening demonstrates that sole listening is not prevalent and listeners are far more likely to also listen to large music brands. This contrasts with Kelly's (2008) 1000 true fans theory. The theory posits that a sustainable living can be earned through 1000 of your hardcore fans each spending $100 a year on your products (e.g. songs/albums, concerts, merchandise). 1000 true fans may be

feasible in theory but far more difficult than acquiring light and infrequent listeners. It is also unreasonable to assume an individual will be loyal to only your music and this is shown to be true, with many listeners consuming a range of other music, in line with penetration. Future research should consider how many fans overall an artist would need in order to get 1000 true fans.

9.7.3. Music stereotypes are dated

This research finds that genres are listened to by audiences with similar demographic and psychographic profiles. This dispels stereotypes that one genre of music is exclusively listened to by a particular type of person. Demographic or psychographic genre targeting may restrict rather than broaden growth potential. Listening to a genre such as Metal does not prohibit listening of other genres. The finding that listener profiles of genres are more similar than different is caused by repertoire and multi-genre listening behaviour, as listeners are unlikely to just listen to one genre. For example, if an individual listens to Blues and Pop then they appear in the listening bases of both genres. Thus, both genres are similarly profiled. This has implications for artists and music marketers/labels. The importance of amassing a wide audience to reach a broad range of music listeners appears to be a feasible pathway to growth.

9.7.4. Play music that people like

The confirmation of a peak in popular music preferences, reflecting tastes acquired during early-to-mid-adolescence (14-15.5 years of age), is of use to advertisers and retailers. Knowledge of when a particular age demographic consumes media or shops, enables advertisers and retailers to select music that approximately reflects their adolescent years. This may enhance the shopper experience or the creative role of music in advertising. However, the full benefits of nostalgia in a consumer context is beyond the scope of this thesis and requires further examination.

9.8. Limitations and Future Research

9.8.1. Self-selection and claimed preference data

The primary data used in Study One consists of only respondents who actively chose to have their music listening tracked. This may therefore lead to self-selection bias and be an incomplete representation of music listening across a general population. Self-selection has been to found to skew towards heavy users (Meyer-Waarden & Benavent 2009) or in this case heavy music listeners. Given that the Last.fm datasets consist of self-identified fans of a core genre (e.g. Classical music listeners), the data may represent the extreme fans of a particular music genre, or heavy music listeners. It could be the case that the self-selected genre (e.g. Classical) dominates each Last.fm dataset and is unrepresentative of a typical music listener. Alternatively, Last.fm users might be heavy music category users who are widely known to buy more brands than light users (e.g. Ehrenberg et al. 1990; Fader & Schmittlein 1993; Sharp et al.

2002). Therefore, Last.fm users could be more omnivorous in their music listening and not represent a normal music listener.

However, the fact that the law of DoP holds and no partitioning is observed, even though the data consists of self-identified fans of a particular genre, could strengthens findings in this thesis. Consequently, the law of DoP should exhibit a superior fit to other behavioural data as it displays an already strong fit to this self-selected data. Future research can consider replication using streaming service (e.g. Spotify) data, should such data become available.

Study Two analyses survey data to compare the listener profiles of selected music genres. A clear limitation of this data is that it is claimed behaviour which may not precisely reflect music listening. However, comprehensive demographic information that is also linked to music listening data is extremely difficult to obtain. Psychographic data is even more difficult to acquire. However, claimed behavioural data (often survey) has been widely used to research music listening (e.g. Dunn et al. 2012; North 2010).

9.8.2. The measurement of genres

Another limitation is the use of genres for assessing music preferences. As noted by Rentfrow et al. (2011), not all artists or musical works can be encapsulated by a single genre, and there is the assumption that research participants are sufficiently knowledgeable about different genres to accurately indicate their music preferences. However, the genres used in this research are derived from Rentfrow and Gosling's (2003) Short Test of Music Preferences (STOMP). STOMP was initially generated following consultation with online music stores and a pre-test demonstrating high familiarity among respondents of all genres. It has also been used in other studies (Delsing et al. 2008; Dunn et al. 2012). Music genres are considered an appropriate measure for music preference as they are the initial level of music preference expression (Rentfrow & Gosling 2003). The listener profile of different artists is an area which is of particular interest for future research. However, this is beyond the scope of this research, which focuses on the listener profiles of genres.

9.8.3. Limited scope

A limitation of Studies Two and Three is that the scope is restricted to the United States. Therefore, findings are only representative of the United States and cannot generalise to other regions. Research should consider genre listener profiles outside of the United States. Study Three is especially limited as only popular music preferences were assessed. Preferences should be assessed using a wider variety of music styles, especially less popular musical works. Research should also investigate the reasons why an age-related popular music preference peak occurs.

9.8.4. Does music follow the NBD-Dirichlet?

Key marketing laws including the law of DoP and similarity in brand user-profiles are captured by the NBD-Dirichlet model (Bass et al. 1976). The model describes how frequently purchased goods are made in a stationary and unsegmented market, although the model still applies to markets not entirely stationary or unsegmented (Ehrenberg et al. 2004). It is able to predict useful Brand Performance Measures (BPM) requiring only brand and category penetrations and purchase frequencies. The model has been successfully applied a number of contexts such as packaged goods (Uncles et al. 1994), durables and services (Colombo et al. 2000; Ehrenberg 1988; Ehrenberg & Bound 2000; Ehrenberg et al. 2004; Sharp 2010), television viewing (Barwise & Ehrenberg 1988) and fruits and vegetables (Anesbury et al. 2018a). Future research should apply the NBD-Dirichlet model to music listening. If music listening behaviour is found to fit the NBD-Dirichlet model, other marketing laws can be applied (e.g. the law Double Jeopardy (McPhee 1963))

9.8.5. Does the Pareto Principle apply to music brands?

The Pareto principle should also be applied to music listening in future research. Early understanding of the principle was that the top 20% heavy buyers of a brand contributed to 80% of its sales (Dubinsky & Hansen 1982). However, empirical findings demonstrate that the sales contribution of the heaviest top 20% of buyers is closer to 50% (Anschuetz 2002; Sharp 2010; Sharp & Romaniuk 2016). This drastically increases the value of light brand buyers. Pending future research, the effective application of the Pareto principle to music brands may discount Kelly's 1000 true fans theory (2008), such that a brands most loyal customers are unlikely to be a meaningful source of sustainable income, as they only contribute to around half of its sales.

Completing NBD-Dirichlet, Double Jeopardy and Pareto Principle analyses will round out the knowledge of listening behaviour, and allow music marketers to use existing knowledge from markets to build more effective marketing plans.

9.8.6. What causes genre listening differences?

Future research should also investigate why some larger demographic differences, such as gender, age and ethnicity are observed in Study Two of this thesis. While this research finds that differences are negligible in aggregate, future research could consider what factors drive the larger differences in music listening. One particular area of interest could be to examine how recommendation systems have impacted music listening. While the success of music recommendation systems has been considered (e.g. Baur et al. 2012; Domingues et al. 2013; Yapriady & Uitdenbogerd 2005), future research could examine whether recommendation systems are perpetuating demographic or psychographic differences in music listening, by making micro-targeted recommendations, or if they contributing to the broad similarity observed in this thesis.

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11. Appendix

11.1. Appendix A: Sub-genre recode list

**Meta-genre appears in bold font

Blues	**Electronica/Dance**	**Metal**	**Rock**	**Pop**	**R&B/Soul/Funk**
blues	electronic	grunge	rock	pop	reggae
bluesrock	trance	industrialmetal	emo	poppunk	disco
Classical	dance	metalcore	indierock	indiepop	soul
classical	house	alternativemetal	punk	britpop	rnb
piano	chillout	hardcore	hardrock	newwave	funk
Country	dubstep	posthardcore	punkrock	dreampop	Ska
country	ambient	numetal	stonerrock	kpop	**Indie/Alternative**
Hip-Hop/Rap	idm	symphonicmetal	progressiverock	MPB	shoegaze
hiphop	industrial	melodicdeathmetal	postrock	Pop Rock	alternativerock
rap	digitalis	gothicmetal	cimxfm	kpop	indie
triphop	downtempo	heavymetal	postpunk	Folk	alternative
	minimal	progressivemetal	psychedelic	singersongwriter	lofi
	upliftingtrance	deathcore	classicrock	acoustic	**Jazz**
	electronica	thrashmetal	psychedelicrock	folk	Jazz
	vocaltrance	powermetal	garagerock	neofolk	bossanova
	progressivetrance	deathmetal	horrorpunk		**Soundtracks**
	electrohouse	metal	southernrock		soundtrack
	techno	doommetal	gothicrock		epic
	psytrance	blackmetal	jrock		instrumental
	drumandbass	piratemetal	christianrock		
	newage	symphonicblackmetal	gothic		
	electro	vikingmetal	ethereal		
	hardstyle	technicaldeathmetal	alternativerock		
	progressivehouse	sludge			
	synthpop	grindcore			
	experimental	progressivedeathmetal			
	electropop	groovemetal			
	darkambient	folkmetal			
		lovemetal			
		darkwave			

11.2. Appendix B: Survey of US sample used for Study Two

Dear Participant,

You are invited to participate in the research project 'factors influencing music preference'. The purpose of this study is to find out more about people's music preferences.

if you would like to know more about this survey click here: [*project info sheet]*. Please confirm if you would like to proceed with the survey:

I agree (proceed)
I disagree (Terminate)

INTRODUCTION:

Thank you for agreeing to participate in this survey. All of your responses are kept confidential.

The survey is about your preference, usage and experience with music. There are no right or wrong answers. We are just interested in your honest opinions and answers.

The survey should take around 15-20 minutes.

The first questions are about you and are for classification purposes.

ADD TO SCREENING QUESTIONS
S1. Have you listened to music of your choosing in the last week?

Terminate if no

○ Yes (1)

○ No (2)

Music preferences and age

Q1 What year were you born in?
Please enter in "YYYY" format e.g. 1984

_____

Q2 What is your gender?

- ○ Male (1)
- ○ Female (2)
- ○ Prefer not to say (3) **[Terminate if selected]**

Q3 Which state do you currently live in?
**insert US state dropdown list*

We would like to ask you some questions about your personality. There are no right or wrong answers.

Q4 How well do the following statements describe your personality?
Please select ONE answer for each statement.

"I see myself as someone who..."
[Randomize order of statements (do not display codes in brackets]

	Disagree strongly (1a)	Disagree a little (2a)	Neither agree nor disagree (3a)	Agree a little (4a)	Agree strongly (5a)
...is reserved (1)	○	○	○	○	○
...is generally trusting (2)	○	○	○	○	○
...tends to be lazy (3)	○	○	○	○	○
...is relaxed, handles stress well (4)	○	○	○	○	○
...has few artistic interests (5)	○	○	○	○	○
...is outgoing, sociable (6)	○	○	○	○	○
...tends to find fault with others (7)	○	○	○	○	○
...does a thorough job (8)	○	○	○	○	○
...gets nervous easily (9)	○	○	○	○	○
...has an active imagination (10)	○	○	○	○	○

We would now like to ask you some questions about your music preferences. There are no right or wrong answers.

Q5 How well do each of these statements reflect your music preferences?
*Please select ONE answer for each statement
[Randomize order of each of the statements on the left-hand side (first column)]

	Strongly Disagree (1)	Somewhat Disagree (2)	Disagree (3)	Neither Agree nor Disagree (4)	Agree (5)	Somewhat Agree (6)	Strongly Agree (7)
⊗I like music that challenges my way of understanding the world. (1)	○	○	○	○	○	○	○
⊗I like music that makes me more reflective. (2)	○	○	○	○	○	○	○
⊗I like music that focuses on meaningful human conditions. (3)	○	○	○	○	○	○	○
⊗My favorite types of music make me think. (4)	○	○	○	○	○	○	○
⊗I am very moved by music that is about people's search for greater understanding in life. (5)	○	○	○	○	○	○	○
⊗I like music that has profound meanings or messages to convey. (6)	○	○	○	○	○	○	○
⊗It's important for me to have fun when listening to music. (7)	○	○	○	○	○	○	○
⊗Music that makes me smile are among my favorites. (8)	○	○	○	○	○	○	○
⊗I find that even simple music can be enjoyable as long as it is fun. (9)	○	○	○	○	○	○	○
⊗I like music that may be considered "silly" or "shallow" if it can make me smile and have a good time. (11)	○	○	○	○	○	○	○
⊗For me, the best music is entertaining. (12)	○	○	○	○	○	○	○
⊗My favorite types of music are happy and positive. (13)	○	○	○	○	○	○	○

Q6a In the last week, roughly how many hours did you spend listening to ANY music of your choice? [Show Hour/Min/Sec in dropdown]

Hour/s

Q6b How did you listen to music in the last week?
Select as many as applicable

- [ ] CD (1)
- [ ] Radio (2)
- [ ] Cassette tape (3)
- [ ] Vinyl (4)
- [ ] Portable OFFLINE music device e.g. iPod, Walkman (5)
- [ ] iTunes (own library) (6)
- [ ] Pirated Music (7)
- [ ] Apple Music (8)
- [ ] Spotify (Paid) (9)
- [ ] Spotify (Free) (10)
- [ ] Pandora (11)
- [ ] SoundCloud (12)
- [ ] Google Play (13)
- [ ] YouTube (14)
- [ ] Other streaming service (please specify) (15)

☐ Other (Please specify) (99)

☐ None of these (100**) [Terminate if selected > only allow this selection if nothing else is selected]**

Q7 In the last week, roughly what proportion of your total time spent listening to music did you allocate to each of these options? E.g. 50% CD
Please note that proportions must total 100%

Insert options selected from Q6b> display box (with % indicated clearly so they do not need to type "%" for each response) that allows respondents to type in a proportion next to each option selected in Q7 > Total must = 100%

e.g. (DO NOT DISPLAY THIS EXACT EXAMPLE IN SURVEY)

Radio	%	50

Q8 Which genres of music have you listened to in the last week? [Randomize order of genre list]

- [ ] Blues (1)
- [ ] Classical (2)
- [ ] Country (3)
- [ ] Electronica/Dance (4)
- [ ] Folk (5)
- [ ] Hip-Hop/Rap (6)
- [ ] Indie/Alternative (7)
- [ ] Jazz (8)
- [ ] Metal (9)
- [ ] Pop (10)
- [ ] R&B/Soul/Funk (11)
- [ ] Rock (12)
- [ ] Soundtracks (13)
- [ ] Other (please specify) (99)
- [ ] None of these (100) **[Terminate if selected > only allow this selection if nothing else is selected]**

Q9 In the last week, roughly what proportion of your total time spent listening to music did you allocate to each of these music genres? E.g. 50% Pop
Please note that proportions must total 100%

Insert genres selected from Q8 > display box (with % indicated clearly so they do not need to type "%" for each response) that allows respondents to type in a proportion next to each option selected in Q9 > Total must = 100%

Pop	%	50

questions about yourself. Please answer as truthfully as
mation is kept strictly confidential.

Q11 Which country have you lived in for the majority of your life?

**insert country dropdown list*

▼ Australia (1) ... Zimbabwe (201)

Q12 Which country did/do you mostly live in during your 20s?
**insert country dropdown list*

▼ Australia (1) ... Zimbabwe (201)

Q13 How many other people live in your household?
Please select one answer.

- ○ None (1)
- ○ One (2)
- ○ Two (3)
- ○ Three (4)
- ○ Four (5)
- ○ Five or more (6)

Q14 How many of those are under 21? [If "None" selected for Q13, DO NOT show this question]
Please select one answer.

- ○ None (1)
- ○ One (2)
- ○ Two (3)
- ○ Three (4)
- ○ Four (5)
- ○ Five or more (6)

Q15 Which of the following best describes your annual income (USD) before taxes?
Please select one answer.

- ○ $19,999 or Less (1)
- ○ $20,000 to $29,999 (2)
- ○ $30,000 to $39,999 (3)
- ○ $40,000 to $49,999 (4)
- ○ $50,000 to $59,999 (5)
- ○ $60,000 to $69,999 (6)
- ○ $70,000 to $79,999 (7)
- ○ $80,000 to $89,999 (8)
- ○ $90,000 to $99,999 (9)
- ○ $100,000 to $124,999 (10)
- ○ $125,000 to $149,999 (11)
- ○ $150,000 to $199,999 (12)
- ○ $200,000 or more (13)
- ○ Don’t know (99)
- ○ Prefer not to say (100)

Q16 What is your race?
Please select all that apply.

- ○ Caucasian or White (1)
- ○ African-American or Black (2)
- ○ American Indian or Alaskan Native (3)
- ○ Asian (4)
- ○ Native Hawaiian or Pacific Islander (5)
- ○ Hispanic/Latino/Spanish (6)
- ○ Other (please specify) (99)
- ○ Prefer not to say (100)

Q17 What is the highest level of education you have received?
Please select one answer.

- ○ Less than high school degree (1)
- ○ High school graduate (e.g. high school diploma or equivalent including GED) (2)
- ○ Some college but no degree (3)
- ○ Associate degree in college (2-year) (4)
- ○ Bachelor's degree in college (4-year) (5)
- ○ Master's degree (6)
- ○ Doctoral degree (7)
- ○ Professional degree (e.g. JD, MD) (8)
- ○ Prefer not to answer (100)

Q18a Are you…?
Please select one answer.

- ○ Employed full time, more than 35 hours per week (1)
- ○ Employed part time, less than 35 hours per week (2)
- ○ Self-employed (3)
- ○ Retired (4)
- ○ College or High School Student (also works part-time) (5)
- ○ College or High School Student (does not work part-time) (6)
- ○ Full time housewife/husband (7)
- ○ Currently unemployed (8)
- ○ Other (please specify) (99)

Q18 Which of the following best describes/described your occupation?
Please select one answer.

- ○ Management (1)
- ○ Business and Financial Operations (2)
- ○ Computer and Mathematical (3)
- ○ Architecture and Engineering (4)
- ○ Life, Physical and Social Science (5)
- ○ Community and Social Service (6)
- ○ Legal (7)
- ○ Educational Instruction and Library (8)
- ○ Arts, Design, Entertainment, Sports, and Media (9)
- ○ Healthcare Practitioners and Technical (10)
- ○ Healthcare Support (11)
- ○ Protective Service (12)
- ○ Food Preparation and Serving (13)
- ○ Building and Grounds Cleaning and Maintenance (14)
- ○ Sales and Related (16)

- ○ Office and Administrative Support (17)
- ○ Farming, Fishing, and Forestry (18)
- ○ Construction and Extraction (19)
- ○ Installation, Maintenance, and Repair (20)
- ○ Production (21)
- ○ Transportation and Material Moving (22)
- ○ Military Specific (23)
- ○ College or High School Student (24)
- ○ Prefer not to answer (100)
- ○ Other (please specify) (99)

We are now going to play short 30 second snippets for 34 songs. You must listen to at least 10 seconds of each song. There are no right or wrong answers.

Q19 Please rate this piece of music.

Import all 34 songs (30 second snippets) with this scale > randomize order > respondents must listen to at least 10 seconds before moving onto next question >

- ○ Don't know
- ○ 0 I dislike it a lot (0)
- ○ 1 (1)
- ○ 2 (2)
- ○ 3 (3)
- ○ 4 (4)
- ○ 5 Neither Like or Dislike (5)
- ○ 6 (6)
- ○ 7 (7)
- ○ 8 (8)
- ○ 9 (9)
- ○ 10 I like it a lot (10)

Have you heard this song before?

>Insert scale on the same page (Q19) for every song above the rating scale

- ○ Yes
- ○ No
- ○ Don’t know/Sounds familiar