Investigating the Influence of the Herding Effect on Consumption Experience: The Case of Online Music

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ABSTRACT

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Zachary Krastel

Social influence has shown to be incredibly powerful in shaping a consumer's behaviour. An example of this occurs with the "herding effect", in which consumers ignore any of their own signals in favour of copying the actions or preferences of the majority. Social influence has been shown to be especially strong in online music consumption, due to the fact that music is highly subjective and can only be ascribed value after it has been experienced; therefore, it is not surprising that strong relationships have been found in research looking at herding effects in music consumption. However, past studies have limited their scope to analyzing the effect across situations, and have so far assumed that the herding effect holds for all consumers, and for all types of music. Therefore, this study looks determine whether there are any potential moderators to the herding effect, such as an individual's personality or the type of music being consumed. Furthermore, while past studies have looked only at product choice as an outcome variable, this study aims to extend our understanding of the strength of the effect to see if it also impacts consumers' subsequent evaluations of the consumption experience. Results suggest this effect on the consumption experience does exist, and significant effects are found that suggest online social connectedness and self-construal moderate the impact of the herding effect. These results have implications for marketers in the music industry, and also more generally for anyone looking to understand how personality may moderate social influence effects.

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INTRODUCTION

It has long been known that social influence can be powerful in influencing people's perceptions and behaviour. Social influence-related phenomena include everything from serious matters, such as the amplification of fears during epidemics (Moussaid et al. 2013) to mundane, everyday decisions, such as in deciding where to sit in a restaurant or what toothpaste to buy (Bikhchandani et al. 1998). In fact, social influence has been shown to even influence what many would consider private, personal decisions, such as in deciding who to vote for, or how many children to have (Banerjee 1992).

In these cases, what often occurs is called an "information cascade", where an individual copies the actions or preferences of the majority, even if it is in conflict with their own preferences. They often do so out of a belief that previous individuals, having already made a decision, must have known valuable information which helped them come to such a decision. When this individual decides to make a congruent decision, the effect is strengthened for the next individual who views the results of these past decisions; the sequential continuation of this process with many subsequent individuals is called the "herding effect".

Herding effects have been shown to be especially powerful in so-called "cultural markets" such as music and movies. These items are often "experience goods", which is a term used to describe the fact that the quality of these products cannot be determined until the consumer has actually experienced the good. Furthermore, the quality of these products is highly subjective – there is not any clearly "good" or "bad" books or movies. Therefore, these products can be especially prone to herding effects, since looking at others' preferences of these goods can help consumers to lessen the burden of having to determine the quality of the goods on their own.

It is not surprising, therefore, that many studies exist which have looked at herding effects in the music industry. Generally, these results have proven music to be an ideal product for herding effects to exist, showing strong relationships between the social information presented along with a song and the likelihood of the song being chosen or acquired by subsequent consumers (Salganik et al. 2006). However, studies up to this point have generally been designed to look at overall effects, assuming that the herding effect holds true for all consumers, and for all types of music. Furthermore, these studies have generally focused on examining product choice, rather than examining in depth what influences the herding effect may have on the subsequent consumption experience.

This study looks to fill these gaps in the literature through an experimental procedure in which social information accompanying the presentation of a song was manipulated to induce herding effects. This was done for a series of five songs, which were chosen based on their ability to represent five separate types of music. Participants' personal preferences for the song were measured alongside their more public intentions to share information about the song with others, in order to compare the effects of the herding effect manipulation between public and private outcomes. Additionally, personality traits of participants were measured using a series of well-studied constructs, in order to determine whether any of these traits moderate the existence or strength of the herding effect.

This study is also valuable due to its focus on analyzing the consumption experience instead of product choice. While product choice is a valuable outcome variable in many consumption situations, understanding how the herding effect affects the actual consumption and subsequent evaluation of the product itself helps deepen our understanding of this effect.

The remainder of this paper details the design, execution, and analysis of this study in order to clearly answer the questions proposed. The following section will begin by providing a theoretical foundation for the study, discussing literature on social influence, the herding effect, and the music industry; the next section continues with a discussion of relevant past research while discussing the measures used in this study. Following this is a statement of the specific hypotheses, followed by a detailed account of the methodology used. Finally, results are presented for each of the hypotheses, followed by a general discussion of these results and their implications for researchers and managers.

THEORETICAL BACKGROUND

The Power of Social Influence

Some of the most fundamental and preeminent psychological theorists have devoted their life's work to uncovering the powerful force that social influence can exert. In particular, the 1950s saw many important advances towards understanding social influence as a powerful phenomenon affecting behaviour. Philosopher Eric Hoffer (1955) noted that when people are free to do as they please, they usually imitate each other. Around the same time, the importance of conformity was clearly demonstrated in a number of important experiments by Asch (1956). He used a series of line judgement tasks to show how individuals lose their ability to trust their own independent opinions when faced with group pressure. Even if they were originally confident that their choice was correct, in the face of conflicting information provided by the group, people feel an overwhelming need to conform to the general group consensus.

Recent research has suggested that this behavioural switch operates because of the creation of a sense of anxiety, which is due to the mismatch between one's preferences and others' (Berns et al. 2010). In fact, Berns et al. (2010) found evidence for physiological manifestations of anxiety, which motivated people to switch their choice in the direction of consensus.

The basic effect initially shown by Asch (1956) and replicated in Berns et al.'s (2010) study has been shown to exist in various situations. Moussaid et al.'s (2013) study is yet another to find this, showing that participants who answered factual questions revised their judgments after being exposed to the opinions and confidence levels of others. Their study uncovered two main mechanisms responsible for such a change in opinion: the first is what they called "the expert effect", in which a highly confident individual acts as a persuading agent to induce a change of opinion. They term the second mechanism "the majority effect", and find that is caused by the presence of a critical mass of people (not necessarily experts) which, when combined, drive the collective opinion in a given direction.

Although not clearly expressed in their article, these mechanisms are essentially analogous to a phenomenon called the "herding effect", which is the focus of the current study. The following section will provide details of this effect and its applications.

Herding and Information Cascades

Research has shown that preferences are often constructed during a decision situation (Ariely et al. 2006; Bettman et al. 1998; Slovic 1995), when a previously-unconsidered choice situation is presented to an individual. In a situation such as this, where an individual has no prior knowledge of the alternatives and has not had sufficient time to conduct an information search, there is no clear "correct" answer, and the individual must rely on other simplifying heuristics in order to make a good decision (Huang & Chen 2006).

An early study by Burnkrant and Cousineau (1975) showed that in situations such as this, people often use others' product evaluations as a source of information about the product. As later explained by Banerjee (1992), this decision is rational because, similar to Moussaid et al.'s

(2013) “expert effect”, the decisions others have made in the past about the product may reflect information that they have and we do not. As we do not feel we have acquired an adequate amount of information in order to make an informed decision, we perceive others’ decisions as an indication of the product’s value, and this influences our own decisions about the product. Research since has found that the relative popularity of products is used in this manner as an indication of both the quality and the appropriateness of the product (Hanson & Putler 1996), suggesting that individuals are not just looking to others in order to learn about the product itself, but also to learn about its potential uses.

After this occurs for a series of consumers in a consecutive fashion, an “information cascade” occurs whereby otherwise rational people “herd” based on the actions of others; each person ignores any signals they may have about the decision, instead imitating the behaviour of the consensus (Eyster & Rabin 2010). Relating to Moussaid et al.’s (2013) mechanisms, what starts out as a perceived “expert effect” on the part of the first few consumers will eventually become a “majority effect”, once the information cascade continues to the point that it reaches a critical mass of people whom have all been influenced in this manner.

Applications of the Herding Effect

The herding effect is essentially a story of self-doubt, observation, and imitation, and the fact that this process involves such fundamental human traits as these makes it easily found in a wide variety of situations. Bikhchandani et al. (1998) mentions many examples in his article on fads, customs and culture: among them are stories of authors purchasing their own books to jumpstart their propulsion onto the New York Times Bestseller List, ancient Roman families hiring professional mourners at funerals, and Hennessy Cognac hiring actors and models to order their product at fashionable bistros.

Academic literature has uncovered evidence of the herding effect in decision situations, such as which stores and restaurants to attend and how many children to have (Banerjee 1992), the decision to adopt new technologies (Kislev & Shchori-Bachrach 1973), the decision to adopt online software (Hanson & Putler 1996), book purchasing that occurs both offline and online (Chen 2008), and even where patrons should be seated in a restaurant (Bikhchandani et al. 1998).

Recent technological advances of the internet have offered a new environment in which to examine herding effects. In fact, the internet is especially prone to herding effects, offering an ideal environment for information cascades to occur by facilitating the ease with which information about other consumers' choices can be retrieved (Duan et al. 2009). This information can include items such as others' reviews of products, their past purchases, and histories of their conspicuous consumption as displayed on social media.

Additionally, the internet has transformed many items – such as books, movies and music – into "information goods", which can be reproduced and stored at zero marginal cost (Shapiro & Varian 1998). This allows online services to provide a nearly infinite catalogue from which consumers can evaluate and choose a product (Anderson 2004; 2006). Presenting consumers with such a staggering number of product options forces them to rely increasingly on heuristics to determine the value of these items, since the cost of evaluating each of them is great (Anderson 2006). Before spending time evaluating each item separately, consumers may look to others as a shortcut to determine what products may be of the best value.

Music

Music's inherent qualities as an information good, an experience good, and a social good make it valuable as a tool for research. This section will detail these terms, and provide an argument as to why use of the online music industry provides a unique opportunity to study social influence.

Music as an Information Good

Before the widespread adoption of the internet, users discovered music through radio play or from their friends, and consumed it through the purchasing of physical albums (Pietz and Waelbroeck 2004). During this time, one of the primary heuristics used to determine the quality of music was terrestrial radio stations, which provided an editorial or "curation" function by only presenting listeners with a limited set of works with which they acquainted their listener base (Waldfogel 2012). The internet has provided a great number of alternative methods of music consumption, and as a result, many consumers no longer listen to the radio, instead opting to use websites like YouTube to discover and listen to music (Nielsen 2013). However, while the internet has since attempted to provide other types of curation functions through the implementation of recommendation engines, social media, and blogs, the impact that this has on actual consumer behaviour – such as sales – is mixed (Dewan & Ramaprasad 2014).

The lack of a curation function becomes an especially important issue when considering that, as an information good, many online music services have created nearly infinite catalogues of music for consumers to choose from (Shapiro & Varian 1998). As with other information goods (see discussion in previous section, above), this "infinite catalogue" means that consumers must rely on heuristics to determine the value of a song before spending time experiencing (and, subsequently ascribing value to) a song (Anderson 2006). Without radio acting as a gatekeeper, consumers must resort to other heuristics to determine which songs to listen to. This makes music an ideal candidate for exploring the effects that heuristics such as social information may have, as the arsenal of other heuristics to which music consumers can resort is especially lacking.

Music as an Experience Good

Music is also an experience good, meaning that consumers can only ascribe accurate value to a piece of music once they have heard – or "experienced" – the song (Bhattacharjee et al. 2003; Regner & Barria 2009; Waldfogel 2012). Without the chance to experience the good, customers risk ending up disappointed with their acquisition or consumption (Regner & Barria 2009). This increases the importance of decision heuristics, since it is costly for a consumer to evaluate each song on her own.

Like other experience goods, there is no inherently "good" and "bad" music, and both quality and appropriateness have been found to be subjective. For example, North and Hargreaves (2005) found that simply labelling a song differently can affect whether it is perceived as "suicide-inducing" or "life-affirming", despite these labels having drastically different connotations and associations. Their study highlights the importance of other cues about the song that may be seen pre- or para-consumption. In the case of the current study, it is therefore expected that social information seen during presentation of the musical stimuli should affect their preference for the song if there is no other information presented that the consumer is able to use in order to make an informed decision.

Music as a Social Good

As referred to above, the lack of an authoritative figure in helping to decide what music should be experienced, the inability to ascribe value to music pre-consumption, and the lack of a general consensus regarding music's quality (even post-consumption) make music especially susceptible to other informational influences – for example, social information that is presented with the music.

Music has been shown to be a "social good", playing a role in the initiation and continuation of social interactions (Kinally et al. 2008). Music has evolved as a means of signaling the cohesiveness of a coalitional group (Hagen & Bryant 2003), and can even play a role in the formation and discontinuation of friendships (Selfhout et al. 2009). This process may work as a way of identifying an individual's potential congruence with the group's or other individual's values, and individuals can use music to portray a particular image – for example, by using music that is congruent with the message they would like to present, they can portray a message of common identification with the group or individual (Larsen et al. 2009).

Recent research in the field of information systems has noted that people can be attracted to use a website because of its perceived sociability – that is, if the site is believed to have implemented the opportunity for social interaction or to receive social information (Junglas et al. 2013). This can be seen in the wide array of sites which have implemented the opportunity for social cues to be present during use, such as how Facebook's ubiquitous "share" button has been implemented on many online websites, or how YouTube has included the number of views a video has received.

Taken together, these findings suggest that consumers should use social information presented with music as a decision heuristic because (1) there are too many choices to be able to evaluate each of them independently and (2) they cannot evaluate a song without listening to it, which is costly; and (3) the social information presented may signal that others may have insight into the "quality" of the music, or (4) the individual perceives that others' consumption of the music is an act of displaying group membership, leading the consumer to form an opinion on the music based on their desire to associate (or disassociate) with the group.

Due to the merits of studying social influence through the lens of the music industry, it is not surprising that studies which examine the herding effect in music consumption have been conducted in the past. The next section consists of a brief discussion of these studies.

Examples in Literature of Herding Effects in Online Music Consumption

Hanson and Putler's (1996) experiment using software downloads showed an early confirmation of the nature of the herding effect in an online environment. Their experiment showed that consumer choice heuristics such as the number of previous downloads attracted some consumers to software which appeared to be the "market leader", inducing further success of the products shown initially to be more popular. Research has since confirmed these results in software (Duan et al. 2009) and online books (Chen et al. 2008), among other products.

Research has also looked to further understand the effect itself, such as Langley et al.'s (2014) study, which looked to delineate "types" of herding. They were able to distinguish herding by conceptualizing the speed of contagion, the number of individuals (i.e., proportion of the population) that follows the herd, and the uniformity of the direction of the herd as variables which can all be involved in the herding effect. This resulted in eight patterns of herding which can exist in online settings, and further analysis by the authors confirmed their existence in a dynamic online environment (Twitter).

The first, and perhaps most seminal, article on herding behaviour in an online music consumption context was conducted by Salganik et al. (2006). The authors created an "artificial music market" by presenting a list of unknown songs to participants, and manipulating the number of previous downloads each song had. Their results were similar to those of Hanson and Putler (1996), showing that the higher the number of downloads a song had, the higher the likelihood that the song would be subsequently downloaded. In other words, increasing the strength of the social influence increased the inequality of success.

Research Since Salganik et al. (2006)

Since the publishing of Salganik et al.'s (2006) article, research on herding in online music consumption has generally been positioned in response to their findings. A follow-up by Salganik and Watts (2008) looked deeper into the long-term effects, showing that a "self-fulfilling prophecy" occurred whereby perceived (but initially false) popularity became real over time. This mirrors findings of previous herding examples, such as one told by Bikhchandani et al. (1998), in which two authors secretly purchased 50,000 copies of their own book from stores around the country to propel their book onto the New York Times Bestseller List. Despite lackluster reviews, and knowledge that the authors had engaged in this behaviour, the book made the bestseller list and continued to stay there without further intervention. Presumably, this occurred because consumers and reviewers learned more from the actions of previous buyers, trusting their collective action (in this case, their continued purchasing of the book) over the other relevant information.

In a direct application of Salganik et al.'s (2006) study, Maecker et al. (2013) showed the robustness of this effect by extending its generalizability to other product categories (movies and scarves) in order to examine non-cultural product domains and those with increased visibility; they also looked at other phases of the purchase decision, including interest, consideration, and actual demand. In all cases, Maecker et al.'s (2013) findings showed that the popularity of the product in question (positive or negative) was amplified by the social information presented.

Scope of the Current Project

Despite the promising findings that herding research has provided in understanding online behaviour in music consumption, research up to this point has generally only looked at understanding the nature of the effect itself. For example, Langley et al. (2014) looked at the types of herding that occurred, while studies following the stream developed by Salganik et al. (2006) have looked at determining what the resulting effects are for the music product (i.e., whether the effect is stable over time), or whether the effect applies to different product categories.

Research in this area up to this point has essentially completely ignored taking taking the perspective of the consumer, aligning with a view common in economics that consumers as a whole act logically and rationally. However, contrary to this belief, individual consumers do not always behave in calculated, rational ways. An extended argument supporting this view can be found in an article by Shafir and LeBoeuf (2002), who conclude that "the rationality critique is compelling and rightfully gaining influence in the social sciences" (p.491). The studies mentioned earlier examine the herding effect as it exists in society as a whole, ignoring any individual variations and differentiations that may exist in consumers in their propensity to being affected by the herding effect. This is not an isolated incident, and indeed, researchers have highlighted the importance of examining consumer personality more frequently and in more depth in consumer research (Baumgartner 2002). In the literature on the herding effect, this may be due in part to the large sample sizes of previous studies (over 14,000 in the case of Salganik et al.'s (2006) paper), which have allowed researchers to ignore these hypotheses altogether.

Therefore, many questions remain: for example, are there individual differences in personality that may cause some people to be more influenced by the herding effect than others? In this case, it could be that some people are strongly influenced by the effect, and these participants make up for the fact that a smaller facet of the population is less strongly influenced. If this is the case, we ought to know; the implications for this are great, since if these hypotheses hold true, managerial decisions made in order to replicate a herding effect may be entirely ineffective against a subset of the population.

The current study follows this argument, looking to fill this gap in the literature by investigating whether any individual differences may moderate the herding effect. In addition, this study looks to confirm the strength of the effect, and see whether it applies to all types of music.

MEASURES

Dependent Variables

The items chosen for dependent variables were predominantly behavioural intention measures, with the exception of one item which measured personal preference. The disruption of the music industry, due to the advances of the internet, has changed the effectiveness of traditional behavioural intention measures in studies examining information goods. It has become culturally acceptable to download and share files for free, regardless of the legality or the traditional view of this behaviour as deviant (Cronin 2009; Hinduja 2008; Vandiver et al. 2012); in fact, in Hinduja's (2012) study, only 14% of participants had never downloaded a pirated music file. Given this, it is not surprising that consumers' reference price (a key component of their willingness-to-pay) has been shown to be influenced by the readily available free goods on peer-to-peer filesharing networks (Makkonen et al. 2011). Therefore, using willingness-to-pay, which has traditionally been a popular behavioural intention measure in consumer behaviour research, would likely be ineffective and inaccurate to include in a study on an information good such as music.

Stein-Sacks (2006) states a belief that just selling the musical content in the future is unlikely to contribute more than 50% to turnover in the music industry, and that instead, marketers should focus on further dissemination of music as a method of artist discovery. Therefore, a series of other measures that relate to dissemination and recommendation were derived which aim to get at these behaviours, due to the fact that these are likely to be of more value in today's music industry.

The dependent variables used in this study were measured through a series of survey questions following the presentation of each song. In order to capture both public and private aspects of preference representing the participant's public and private "self" (Triandis 1989), these questions consisted of both questions about their personal preference and about their intentions of sharing the song with others. These are presented in separate sections, below.

Personal Preference

The first group of dependent variables, which are termed here "personal preference", aim to uncover participants' private, personal preferences at the individual level. First, participants were asked to rate how much they liked the song, on a scale from 0 (not at all) to 100 (very much). This is similar to the question used to measure preference in Rentfrow et al. (2011), except in their case they utilized a 7-point scale; for this study, it was decided that increased specificity of the preference variable would be desirable for the purposes of analysis.

Additionally, participants were asked about their personal behavioural intentions for each song. First, participants were asked their likelihood of downloading the song, should it be made available to them now. Although many business models for music exist online that do not require actual downloading or acquisition of music (such as online music subscription-based models – see Teece 2010), some consumers remain emotionally connected to ownership of music (Styvén 2010), and therefore this item may have some effect for those who continue to value ownership of music. Additionally, this was collected in conjunction with another item which may be more familiar to users of non-acquisition-based music business models: participants were also asked the extent they would be likely to listen to the song again, should they come across it at a later time. These items were both measured on 7-point scales (0 = not at all, 7 = to a great extent).

Intention to Share

The second group of variables, termed here "intention to share" relate to participants' willingness or intention to disseminate information about the song to their peers. First, participants were asked about their intention to spread word-of-mouth; while this is sometimes seen as a competing variable to the herding effect in that both can influence an individual to conduct a behaviour (Duan et al. 2009), word-of-mouth is utilized here as a dependent (outcome) variable, in order to measure the propensity that the individual will engage in future word-of-mouth recommendations of the song. In order to operationalize this concept, participants were asked the extent to which they would be likely to recommend this song to (1) a friend, and (2) a relative, on 7-point scales (0 = not at all, 7 = to a great extent).

In a similar manner, participants were also asked about their likelihood of conducting behaviours on social media, were they to come across the song in that setting. Studies investigating behaviour on social media have looked to differentiate consumers based on those who are "active communicators" versus those who are "passive consumers" of content (Yeo 2009); therefore, behavioural intentions relating to both ends of this continuum were measured by asking the extent to which participants were likely to "like" a post of the song, and also the extent they were likely to re-post the song (i.e., "share" it), should it appear on their social media account. These questions were also measured on 7-point scales (0 = not at all, 7 = to a great extent).

Potential Moderators

After an evaluation of relevant literature, four constructs were identified as potential moderators of the herding effect: online social connectedness, self-construal, need for uniqueness, and susceptibility to normative influence. The remainder of this section discusses the literature on these topics. All potential moderators were measured using a series of 7-point scales to uncover the construct, with all scales using anchors at 0 = "not at all", and 7 = "to a great extent". The individual items used for each of these scales are presented in Appendix A.

Online Social Connectedness

Kohut (1971; 1977) originally proposed a psychological theory that the self was composed of two needs: grandiosity and idealization. He later modified this to include a third major need, which he called the need for an alter ego, or "belongingness" (Kohut 1984), defining it as "a sense of belongingness or 'being a part of' in order to avoid feelings of loneliness and alienation… [t]his sense of connectedness allows people to maintain feelings of being 'human among humans' and to identify with those who may be perceived as different from themselves" (p.200). This theory was later adopted by Lee and Robbins (1995), who built on Kohut's (1984) theory of belongingness to develop reliable and valid self-report measures for each of the three aspects, including social connectedness. Their revised version of the scale (Lee et al. 2001) has proven reliable in studies since, and continues to be used in research on social connectedness (for example, in Grieve et al. 2013).

Köbler et al.'s (2010) research was among the first to look at social connectedness in an online environment by investigating how the use of status update messaging generates a feeling of connectedness between users. They found that the more individuals use the technology to reveal information about themselves, the more connected they felt; they used these findings to suggest that the psychological need for connectedness may explain the popularity of social networks such as Facebook (Köbler et al. 2010).

Grieve et al. (2013) built upon this idea by asking whether a person's feeling of social connectedness online is necessarily the same as their feelings of social connectedness offline, hypothesizing that the developing of a sense of online connectedness may not replace a person's state of low social connectedness when in a face-to-face environment, for example. They did this by adapting Lee et al.'s (2001) social connectedness scale to be used in an online environment, and comparing the two scales. Their results showed that the two were not correlated, and they concluded that connectedness developed online (on Facebook, in their case) was separate and distinct from offline social connectedness.

Because this study is examining social connectedness as a potential moderator in an online consumption context, it does not make sense to involve a measurement of the offline construct; therefore, this study uses a subset of five items from Grieve et al.'s (2013) online social connectedness scale, which were chosen based on the reliability scores for the scale items as presented their study.

Self-Construal

In a paper examining "cyber-conformity", Cinirella and Green (2007) found that participants from collectivistic nation manifested greater conformity in computer-mediated contexts (CMCs), even when they were studying and living in a more individualistic nation. This finding is consistent with literature on individualism and collectivism (see Hofstede 1980), a dualism that is often used in studies examining cultural differences. Markus and Kitayama (1991) solidified this concept by referring to a trait termed "self-construal": people with an independent view of themselves (often from Western countries) see themselves as separate, unique, and value internal attributes; on the other hand, people with an interdependent view of themselves (such as those from East Asian countries) see themselves as part of a whole and connected to others, place importance on social context, and value relationships with others.

Although tempting to view this as a continuum on which a person that is low in independence is also high in interdependence, there is some theoretical and empirical evidence that this is not the case; a person could potentially express either trait, depending on the situation (Singelis 1994). Triandis (1989) suggested that this may be due to the self acting as a mediating variable, in which the private (idiocentric), public (allocentric), and collective (group) self could all play a role in developing cognitions when confronted with a social situation. This study focuses on the private and collective selves, and uses a measure developed by Singelis (1994), originally consisting of a scale of 24 items; 8 items (4 interdependent and 4 independent items) were chosen from this scale, based on the factor loadings of the items in Singelis' (1994) study.

Need for Uniqueness

The concept of self-construal works well to identify large-scale differences that may occur in consumers' self-view when on a macro scale – for example, when examining differences between cultures. However, even within each dimension (for example, within those high on the independence trait), differences can exist in the intensity of individuals' desires to be unique and distinct from others through, for example, their purchase and visual display of unique products or goods.

Tian et al. (2001) identified this need as a "pursuit of differentness" or a "counterconformity motivation", and developed a measure to capture an individual's need for uniqueness. Within this construct they conceptualized three behavioural manifestations (dimensions): "creative choice counterconformity", which is the level to which a person purchases original, novel, or unique consumer goods; "unpopular choice counterconformity", which refers to the selection or use of products and brands that deviate from group norms as a method of differentiation from others; and "avoidance of similarity", which refers to consumers' loss of interest and discontinued use of items that have become commonplace – this includes their avoidance of purchasing already commonplace items (Tian et al. 2001).

This study focuses on participants' reactions to an item (a song) that is presented to them, and there is no opportunity for selecting within a group of items; therefore, only the third manifestation (avoidance of similarity) was used in this study as a potential moderator. Of the 9 items in the original scale, 4 items were chosen for inclusion in the current study; because the original items were focused on participants' product and brand consumption behaviours, these items were adapted to a music consumption context. For example, "When a product I own becomes popular…" was adapted into the statement "When music I listen to becomes popular…".

Susceptibility to Normative Influence

Although the findings of Asch's (1956) study on social influence using the line judgment task are impressive, not all participants in the study demonstrated equal susceptibility to the social influence manipulation. This is acknowledged in McGuire's (1968) review of empirical findings of interpersonal influence, where he notes that susceptibility to influence is a general trait that varies across the population. This finding led Bearden et al. (1989) to develop a scale for measuring consumers' susceptibility to interpersonal influence.

Resulting from Bearden et al.'s (1989) study was a 12-item, 2-factor scale that encompasses consumers' susceptibility to both normative and informational influences. This dual structure is consistent with findings from other research on interpersonal influence, such as Burnkrant and Cousineau's (1975) study. In the current study, 5 items from the original 12-item scale were used, including items from both the normative and informational scale.

Control Variables

As will be discussed below, songs which were not familiar with participants during the pretest were specifically chosen for this study (see the section on music stimuli development in the Methodology section for an extended discussion on this topic). However, because songs were obtained based on their current existence on YouTube, it remained possible that participants may have encountered the song before. Therefore, a question asking their familiarity with the song was asked after it had been presented. Unlike the pretest, in which a scale of familiarity was provided, participants in the final experiment were instead given a binary response option (0 = no, not familiar; 1 = yes, familiar).

Participants were also asked about their music listening habits as control variables. Specifically, they were asked about the frequency with which they listen to any music, music on YouTube (related to the study setup, which involved the creation of a YouTube-like interface), and new music (to control for their familiarity with experiencing and evaluating new music).

Although no explicit hypotheses were developed based on demographic information (apart from any effects of cultural origin), age and gender information were also gathered to be used as control variables.

HYPOTHESES

As will be discussed in more detail in the "Methodology" section that follows, the main setup of the study involved a procedure in which the social information (the number of "likes" or previous views a song has) presented with a song is manipulated. Considering this study's main research questions, and using the measures discussed above, the following three hypotheses were proposed; hypotheses are presented below in reference to the two main groups of dependent variables discussed above – namely, preference (private) and intention to share (public).

Hypothesis 1

As an important first step, we must investigate to see that the basic experimental manipulation – namely, the creation of the herding effect – has occurred. Therefore, the first hypothesis looks at whether this manipulation has been replicated in a manner similar to previous herding studies.

H1a: When social information presented with the song is high, participants will report higher preference for the song than when the social information is low

H1b: When social information presented with the song is high, participants will be more likely to share the song than when the social information is low

Hypothesis 2

Generally, there has been little consensus in deciding upon clear categories of music (Aucouturier & Pachet 2003); however, a series of studies by Rentfrow et al. (2003; 2011; 2012) have developed five music factors, forming the acronym "MUSIC", and this delineation of types of music are used in this study. More details of this study's methodology and the validity of the factors' use in this study will follow in the "Methodology" section below.

Studies looking at music herding have, up to now, not investigated whether the herding effect differs depending on the type of music. Therefore, no specific hypotheses can be formed regarding differences in the the herding effect's strength for different types of music, and the research conducted in this regard remains exploratory.

H2a: The social information will have a similar effect on preference for all types of songs (i.e., Mellow, Unpretentious, etc.)

H2b: The social information will have a similar effect on intentions to share for all types of songs (i.e., Mellow, Unpretentious, etc.)

Hypothesis 3

Finally, individual differences in personality may moderate the herding effects found. For simplicity, only one hypothesis is presented for each moderator – however, results will continue to be examined for each of the two groups of dependent variables separately, as was shown in the previous hypotheses. As discussed above, the individual differences investigated in this study are online social connectedness, self-construal, need for uniqueness and susceptibility to social influence.

H3a: As social connectedness level increases, the strength of the manipulation will increase, with songs presented with high social information being rated more favourably than those presented with low social information

H3b: As level of interdependent self-construal increases, participants presented with high social information will show higher preference for the song than those presented with low social information

H3c: As level of independent self-construal increases, participants presented with high social information will show lower preference for the song than those presented with low social information

H3d: As level of need for uniqueness increases, participants presented with high social information will show lower preference for the song than those presented with low social information

H3e: As level of susceptibility to normative influence increases, participants presented with high social information will show higher preference for the song than those presented with low social information

METHODOLOGY

In order to test these hypotheses, an experimental procedure needed to be designed in which social information could be manipulated, while at the same time maintaining ecological validity as much as possible. This section will cover the design and implementation of the tools and stimuli needed to answer these research questions.

Development of Audiovisual Interface

Reasons for Replicating YouTube

In order to relate the experimental procedure to a real-world consumption situation as realistically as possible, a YouTube-like interface was chosen. There are many reasons why this is a valid choice for this study, but chief among them are recent findings that YouTube has become the most popular way for young people to discover new music (Nielsen 2013). Since our sample was limited to undergraduate students, this is ecologically valid as it relates to a consumption environment with which they are likely to be familiar.

Additionally, YouTube is an ideal consumption situation for this study because it integrates a social component into the music-listening experience; this is done through presenting the number of "views" a video has, as well as the number of "likes" it has received from previous viewers in comparison to "dislikes". Assuming that many of the participants are likely to be at least somewhat familiar with this interface makes it an ideal vehicle to manipulate the presented information in order to artificially create a herding effect.

Finally, utilizing YouTube's "embed" function also allowed for the implementation of the songs into the survey in a manner that addresses copyright issues.[1]

Development of the Interface

YouTube created its "embed" function as a way for website owners to include YouTube content on their web pages without forcing the web owners to send visitors away from their site in order to view the content. However, this function limits what is embedded to its essential elements – mainly, the video player itself – and does not transfer the social information to the embedded location.

In order to replicate the herding effect, the social information should be manipulated in an environment that is as close to reality as possible. Therefore, the YouTube website was re-created through the use of graphics software and HTML coding, in conjunction with the original "embed" function. While quite similar to YouTube, some key elements (such as the "recommended videos" sidebar) were removed from this web page in order to focus participants on the elements that are key to this study. What remained was limited to the video and its controls, the basic branding of the site, and the social information positioned directly underneath the video.

In order to avoid confounding effects of participants cognitively evaluating the music videos normally presented with songs on YouTube, the video portion of the embedded video was overlaid with a neutral video of a simulated star-scape; therefore, the web page for each song was essentially identical except for two elements: first, the name of the song and the artist was presented underneath the video player, in order to maintain a similar appearance to the regular YouTube site; second, the social information was changed to be either high or low. These numbers were chosen based on objective evaluations of the average values for songs on YouTube. See table 1 below for the values assigned to each condition; numbers within these ranges were assigned to each song randomly.

[1] YouTube's current legality and compensation structure (see information provided by YouTube here: https://www.youtube.com/yt/copyright/index.html) assumes that anyone who uploads a video onto the site does so as the sole rightsholder, or at least does so with the permission of the rightsholders. If a rightsholder discovers that one of their videos has been uploaded without their permission, they have the right to either (1) request the video be taken down; (2) allow the video to remain, but add advertisements as a method of monetizing its continued distribution; or (3) waive their rights to the video. Therefore, any video remaining on the site can be assumed to be there legally. Since playing a song embedded into a website (or survey, in this case) is a method of playing a song through YouTube itself, any plays – or "distribution" of the song – done through this method is also done so legally.

Table 1
Values for Social Information Manipulation

Social influence	Views	Likes	Dislikes
High SI	1.1 - 1.4 million	20,000 - 26,000	175-325
Low SI	1,100 - 1,400	20 - 30	20 - 30

Development of Musical Stimuli

Background on Music Genre Categorization

As stated above, Hypothesis 2 aims to see if there are differences in the strength of the herding effect based on the type of music. However, there is no clear delineation of "types" of music, and many previous attempts to define genre and obtain consensus on their definitions have failed (Aucouturier & Pachet 2003). Despite this, a study by Rentfrow & Gosling (2003), and a more robust follow-up study (Rentfrow et al. 2011) attempted to take on the colossal task of music categorization through analysis of preference data. Specifically, they used factor analysis to uncover a latent 5-factor structure underlying music preferences, with the five factors represented by the aptly-suited acronym "MUSIC" (Mellow, Unpretentious, Sophisticated, Intense, and Contemporary). Follow-up studies have found this structure to be robust and reliable (Rentfrow et al. 2012), and age-invariant (Bonneville-Roussy et al. 2013). Their studies also investigated how a series of sound-related attributes, psychological attributes and genres correlated to each of the five factors.

Rentfrow et al.'s (2011; 2012) five-factor structure (hereafter referred to as "MUSIC factors"), was utilized in this study as a method for limiting the number of types of musical excerpts that would have to be tested to satisfy H2a and H2b. Furthermore, since this factor-analytical method uncovers latent (and therefore already-existing) patterns in music preference data, this structure is more valid in explaining patterns of music preferences than using other methods of music classification, such as a manual or prescriptive genre-classification approach (Aucouturier & Pachet 2003).

Choice of Musical Stimuli

In order to identify valid musical stimuli, four decision factors were employed. First, it was important that the songs and musical artists used could not be easily identified by participants, in order to control for any previous associations they may have that could affect their judgments of the songs. This was controlled for by referring to Rentfrow et al.'s (2011) studies, of which some experiments used previously-unknown songs chosen by independent musical experts; when possible, songs from these studies were chosen, however if a particular song was unavailable, another song from the same artist was preferable as it was assumed that the styles of the songs were likely to be similar within-artists.

Second, each song had to characterize one of the five MUSIC factors, while simultaneously not significantly characterizing any of the other four factors. This was done by again referring to Rentfrow et al.'s (2011; 2012) studies; between these two articles, three of the experiments used previously-unknown songs, and the same songs were often used more than once. Comparing factor loadings of each song across multiple studies acted as a pseudo-test of reliability for the factor loadings, indicating whether each song was consistently perceived as belonging to its respective factor. Songs and artists which had consistent factor scores, clear factor loadings and high loadings on their respective factors were favoured as potential stimuli.

Third, the design of both the pretest and the final experiment required that the song be available on the popular online website YouTube. Because the songs were chosen based on the fact that they are not likely to be known by participants, it was not surprising that we could not find some of the chosen songs (or even artists) on the site; when this occurred, songs were located and listened to on the online database from which Rentfrow et al. (2011) acquired the songs for their stimuli sets[2], and similar songs were subsequently identified and chosen based on the subjective evaluations of the researchers. This subjectivity was not perceived to be an issue at this stage in the stimuli development, as a pretest was planned to confirm all aforementioned aspects of the stimuli. The final list of 25 songs is presented in Table 2, below.

Lastly, songs with neutral preference ratings were preferred over songs with positively- or negatively-skewed ratings. A subsequent pretest was run in part to control for this, as well as to confirm aspects of the other two decision factors.

Rentfrow et al. (2011) used 15-second excerpts of each song in their studies; however, it was decided for this study to use 45-second excerpts in order to allow for more time for participants to evaluate the online environment of the song – specifically, the web page including the social information manipulation. The online music downloading service iTunes creates 30-, 60- or 90-second clips of each song it sells on its service, and usually chooses a representative

[2] Getty Images database – http://www.gettyimages.ca/music/collection

sample of the song (i.e., usually part of the chorus and a verse). Since all songs chosen for the study were available on iTunes, excerpts roughly corresponding to the portion of the song presented on iTunes were chosen to be the excerpts used in this study.

Table 2
List of Music Stimuli Evaluated in Pretest

Factor	Song #	Title/Artist	Genre
M	M1	Skin & Heart & Lungs (Language Room)	Soft rock
	M2	All I See Is You (Lisa McCormick)	Adult contemporary
	M3	Better than Nothing (Sarah Jaffe)	Soft rock
	M4	Let's Go Down (Aiden Moore)	Indie rock, folk
	M5	Soul On Soul (Rick Braun)	Smooth jazz/R&B
U	U1	Penny Black (Bob Delevante)	New country
	U2	That's Not Rockabilly (Hillbilly Hellcats)	Rock-n-roll
	U3	Lazy Afternoon (Carey Sims)	Mainstream country
	U4	All I Can Give to You (Anna Coogan & North 19)	Bluegrass
	U5	All My Money On You (Diana Jones)	Bluegrass
S	S1	Concerto in C (Antonio Vivaldi)	Classical
	S2	For P (Ilya Truhanov)	World, folk
	S3	One for Daddy-O (Cannonball Adderley)	Traditional jazz
	S4	Samba de Orfeu (Nos Quatro)	Latin
	S5	I've Never Been In Love Before (Jeff Hamilton Trio)	Traditional jazz
I	I1	Death Before Dishonor (Five Finger Death Punch)	Heavy metal
	I2	Over Now (Straight Outta Junior High)	Punk
	I3	Out of Lies (Dawn Over Zero)	Heavy metal
	I4	Cost of Your Loss (Mojo Radio)	Classic rock
	I5	Human (32 Leaves)	Heavy metal/hard rock
C	C1	Immaculate (Mykill Miers)	Rap
	C2	Valkyrie (The Crüxshadows)	Electronica/pop
	C3	Swagg Against Da Law (Shiest Boogey)	Rap
	C4	Trials and Tribulations (Cary Kanno)	R&B/rap
	C5	Hey Young World (Ruckus Fo'Tet)	R&B/rap

Sample

Undergraduate student participants were recruited to participate in this study. Once arriving and agreeing to participate, they were seated at private, individual computer stations to complete the survey. This sampling procedure was used for both the pretest (N = 31) and main experiment (N = 135).

It can be noted that taking a position of this age range as a limitation of the current study has limited merit, for numerous reasons. People within this age range listen to music significantly more than older consumers and listen in a wider variety of contexts (Bonneville-Roussy et al. 2013), form a significant portion of the music fan base (Bhattacharjee et al. 2003), and are responsible for more than one-third of all single album sales in the US – this could perhaps be an even greater proportion when online digital purchases are included (Berns et al. 2010).

Furthermore, young people are believed to be highly responsive to social influence (Steinberg & Monahan 2007). Therefore, any effects that do exist in herding of music consumption are likely to be more evident through the use of this age group, due to their interest in the music used as a stimuli, as well as their increased responsiveness to the differences in social information used here as an experimental manipulation.

Pretest of Music Stimuli

Procedures

The purpose of the pretest was (1) to provide a test of the audiovisual interface, and (2) to further pare down the number of songs used as musical stimuli. Based on the methods discussed previously, a subset of 25 songs were chosen (constituting 5 songs for each MUSIC factor) and integrated into the interface.

Thirty one participants were brought to the lab and seated at individual computers equipped with a set of headphones. Each participant was presented with one of the 25 songs at random, after which they were asked a series of questions in reference to the presented song; they then repeated this procedure for all 25 songs.

After presentation of each song, participants were asked to indicate whether they were familiar with the song, their degree of liking of the song (single-item, 7-point – Rentfrow et al. 2011), attitude toward the song (3-item, 7-point semantic differential), enjoyment of the song (single item, 7-point – various sources such as Raghunathan & Corfman 2005; Mandel & Nowlis 2008), and stimulus arousal (3 item, 7-point semantic differential scale – Di Muro & Murray 2012). They were also asked the extent to which they believed the song represented the list of 22 sound-related and psychological attributes found in Rentfrow et al. (2011), to compare to their findings. Finally, as a control factor, they were asked to rate their mood after each song (a series of 7-point scales: 4 likert-type and 5 semantic differential – Mehrabian & Russell 1974).

Results

After removing participants that experienced technical issues, 25 participants remained in the sample used for analysis of the pretest. Due to the extensive and repetitive nature of the pretest, only 15 respondents finished the survey and listened to all 25 songs; however, further analysis showed no significant differences in the results of any of the measures between those who did and did not complete the survey, so the larger sample was retained for analysis.

Songs were evaluated based on four aspects. First, familiarity was measured on a 4-point scale (0 = not familiar, 4 = song is known well); average scores were calculated for each song, with lower scores being preferred over higher scores. Next, preference scores were evaluated by centering the data based on the median value of the 7-point scale, therefore higher scores (positive integers) indicated that participants generally rated liking the song, while lower scores (negative integers) indicated general dislike for the song. Where possible, scores closest to zero were preferred; however, in the case that this was not possible, a positive value would be preferred over a negative value.

Participants were also asked to characterize the song's genre. First, they were asked to choose one of 17 genres to represent each song – these 17 genres are divided between the five MUSIC factors. Percentages were calculated for: (1) participants that chose a genre within the correct factor; (2) participants that also chose the correct genre within the correct factor; and (3) participants that did not choose the correct factor. Generally, choosing any genre within the correct factor was seen as a more important judgment than choosing the correct genre itself, as the latter judgment is more specific than is needed for the purposes of this study. Finally, participants were asked to state the extent to which the song was characteristic of the genre they chose, on a 7-point scale. Similar to the method for preference ratings, this was analyzed by centering the data on the median value of the 7-point scale; therefore, positive integers indicated participants as a whole were generally confident in their choice of genre, while negative values indicated lack of confidence. Higher scores for those who chose the correct factor and genre (and lower scores for those who did not choose a genre within the correct factor) were preferred as this indicated confidence in the correct choice (and lack of confidence in the incorrect choice). However, this analysis was only taken into consideration if the previous (above) analyses were not able to yield a clear consensus.

Based on these results, 5 songs were chosen for the final experiment; these songs are presented in Table 3, below.

Table 3
Final List of Music Stimuli

Factor	Title/artist	Genre
M	All I See Is You (Lisa McCormick)	Adult contemporary
U	Lazy Afternoon (Carey Sims)	Mainstream country
S	I've Never Been In Love Before (Jeff Hamilton Trio)	Traditional jazz
I	Cost of Your Loss (Mojo Radio)	Classic rock
C	Valkyrie (The Crüxshadows)	Electronica/pop

Procedures for Main Experiment

The main experiment involved 135 student participants in an environment identical to the pretest. All participants were required to listen to the same 5 songs, which had been chosen based on the results of the pretest (see above). These songs were presented in random order, and their social influence condition was also assigned randomly but evenly across all the conditions, alternating high- with low-social information songs; for example, a participant who started with a high-social information song would next see a low-social information song, followed by a high-social information song, etc. until all five songs have been shown. Thus, the final study was a 5 (songs: each of the MUSIC factors) x 2 (social information: high or low) experimental design, where music occurred within-subjects, and social information occurred for each song between-subjects.

At the beginning the survey, participants were informed that they would be listening to 5 of 6 songs which were presented in a list on the same page. The songs were listed here with their social information (number of views), as an attempt to strengthen the manipulation; the sixth song was a song not used in the study, but was presented here in order to balance the social information presented – for example, if the participant was to be shown 3 high-social information songs and 2 low-social information songs, the sixth song would be presented with low-social information.

The next part of the survey consisted of the presentation of each of the 5 songs. Following each song, participants were asked a series of questions to determine their preference for the song. The mood of the participants was measured as a control variable both at the start of the survey and after they had finished listening to all 5 songs.

Once they had finished listening to the songs, they spent approximately 20 to 30 minutes completing a series of unrelated tasks. After completing these tasks, they were asked questions about their personality and demographics, in relation to H3.

RESULTS

Descriptive Results of Main Experiment

The main experiment consisted of data gathered from 135 participants as part of a larger, unrelated study. After removing invalid data (i.e., those who did not follow procedures correctly or those who had technical issues during the survey), 123 participants remained. This sample was used for the remainder of analyses discussed here.

Participants had an average age of 21.17 years old (standard deviation = 1.83), reflecting the undergraduate student population from which this sample was recruited, and 48.7% of participants were female. 24 participants had spent more than 80% of their life outside Canada – this statistic reflects the ethnic heterogeneity of the sample, which is important to note when considering that one of the experimental variables (self-construal) can be linked to ethnic origin (Markus & Kitayama 1991), and therefore a high level of variance in this variable is preferable.

The sample were generally heavy music listeners: 61.3% of participants reported listening to music at least once per day; further, 48% of participants reported using YouTube to listen to music at least once per day, supporting Nielsen's (2013) findings that YouTube has become a popular way for young people to listen to music. 33.6% of participants reported listening to music that is new to them at least once per day – however, this number increases to 74.7% when including participants that listen to new music at least once per week.

Taken together, these results suggest that this sample listens to music frequently, seeks variety in this music consumption, and is well-suited to experiencing a situation (such as the experimental manipulation in this study) that mimics a music discovery scenario on YouTube.

Controlling for Order Effects

The experimental procedure, as explained above, involved presenting all five of the songs in random order to each participant. Although this procedure was advantageous in that it allowed for the possibility of within-subjects analysis and allowed for an increase in the number of ratings for each song, this design also introduced the possibility for order effects to occur. This section details the analysis that was completed to investigate this question.

Analysis consisted of ANOVAs which examined the two computed dependent variables based on two independent variables: the social information condition exposed to (low or high social information), and the order of the song. The latter variable had five possibilities, representing the five spots in the stimuli order in which the song could appear to participants. Results initially suggested that order effects significantly interacted with the condition to explain the dependent variable for all songs, with the exception of song C. Further post-hoc tests showed that in most cases, this significant relationship existed whenever a song followed song C in the order. One interpretation of this result is that this song created an effect in which the following song was evaluated in comparison to song C. While there could be many reasons why this is the case, such as melodic or rhythmic memorability of the song, it could also be that participants particularly disliked the song, and that this affected their subsequent judgments by rating the following song more favourably: the average preference score of song C was lower than all other songs, and this difference was even marginally significant between songs U and C ($t(122) = 1.722$, $p = .088$).

Since it was possible that song C was affecting results of other songs that followed directly after it, it was decided that in cases in which a song followed C, its evaluations (dependent variable scores) should be removed from analysis. Analysis was also run to see whether there were significant differences between the first song rated and the subsequent songs, however there was no significant differences for any of the songs based on this. Therefore, apart from the effect of song C, no other order effects were found to exist.

Scale Reliability

This section reports the reliability of the scales used in this study. Initially, factor analysis was used to confirm that the factor structure of each construct conformed to expectations based on the results from previous studies using the measure. The model was set to retain all eigenvalues greater than 1.0, following Kaiser's rule (1959) – however, following the recommendations of Horn (1965), the absolute nature of this rule was not followed, and eigenvalues nearing the 1.0 cutoff value were considered. After the factor structure was confirmed, a reliability analysis using Cronbach's alpha was performed to test the reliability of the scale as a whole.

Select items within each scale were reverse-coded when presented to participants, as a method of quality-control for their responses. In the case where their responses for these questions were illogical and obviously in contradiction with their previous responses, their responses were analyzed in more detail, and where appropriate, were removed from analysis. Item coding was corrected to align with the original direction of the scale before running the aforementioned analyses. Below are details of the results of the reliability analysis for each of the personality scales used.

Online Social Connectedness

The scale presented to participants for online social connectedness consisted of five items; four of these items loaded on one factor (eigenvalue = 2.45, 48.94% of variance explained), while one item ("I feel like an outsider when online") loaded on a separate factor (eigenvalue = 1.08, 21.5% of variance explained). This item was one of the reverse-coded items, and it was perceived to be troublesome and not representative of the overall construct since the other items loaded strongly on the first factor. Therefore, this item was removed and the factor analysis was re-run; this resulted in a strong one-factor structure (eigenvalue = 2.23, 55.78% of variance explained).

Next, a reliability analysis on the remaining four items was conducted, resulting in a Cronbach's alpha value of ca =.73; this falls within the suggested cutoff value of ca =.70 suggested by Nunnaly (1978), and thus, this final four-item scale was considered reliable.

Self-Construal

The literature on self-construal suggests analyzing this construct as two separate scales representing inter- and independence (Singelis 1994). Therefore, an initial factor analysis of all items within the self-construal scale was conducted in order to observe their combined factor structure. Following the procedures used in Singelis' (1994) study, Promax rotation was used as it was believed that the two factors could be correlated. The initial result was a three-factor structure, with the interdependent items loading on a single factor, and the four independent items loading on two separate factors. However, because the third eigenvalue was near the cutoff value of 1.0 (eigenvalue = 1.04) and the last two factors accounted for a small percentage of the variance when separate, it was decided to force a two-factor structure to reflect the general consensus in the literature mentioned above. After this was completed, the items loaded on their respective factors cleanly (i.e., all independent items loaded on the "independent" factor, etc.).

Next, a factor analysis was calculated for the interdependent items alone. A relatively low percentage of variance was accounted for by these four items (eigenvalue = 1.85, 46.11% of variance explained); however, the scree plot (Cattell 1966) and value of the second eigenvalue (.891, not close to 1.0 as recommended by Kaiser (1959)) suggested this factor structure was sound. Next, a reliability analysis was run on these four items: Cronbach's alpha was also low, (ca =.60), however the removal of any individual item (as shown by the Cronbach's alpha-if-deleted statistic) would not have increased the overall reliability of the scale. Therefore, the scale was retained – however, the weakness of this scale should be noted as a limitation of the current study's findings as they relate to interdependent self-construal.

Next, a factor analysis for the independent items was conducted. When calculated alone, these four items loaded on one factor (eigenvalue = 1.88, 46.87% of variance explained). A subsequent reliability analysis showed results slightly stronger than the interdependent items, with a Cronbach's alpha value of ca = .62. However, this item still falls below recommended values (Nunnaly 1978) – therefore, again, results of this reliability analysis should be taken into consideration when interpreting the results of this construct in further analysis.

Items for each of the two scales were combined into independence and interdependence scores, and a correlation analysis of the two items was run. Results showed that the two items were not correlated (r = .069, sig. = .45), confirming Singelis' (1994) position that the two items are independent of each other.

Need for Uniqueness

A factor analysis run for the need for uniqueness construct showed strong results for a one-factor solution (eigenvalue = 2.32, 58.06% of variance explained), and a subsequent reliability analysis showed a sufficient Cronbach's alpha value (ca = .74). Therefore, it was concluded that this scale was reliable.

Susceptibility to Normative Influence

As expected, the results of a factor analysis of all items in this scale resulted in a two-factor solution, and loadings were consistent with the division of items between the normative and informational influence constructs. However, the second factor (informational influence) was weak; this is not surprising, given that correlations between the informational measure and other related variables (including behavioural indices and measures of motivation to comply) was not strong in Bearden et al.'s (1989) study on this construct; they found that the correlations between the normative dimension and these other measures were consistently stronger than the correlations involving the informational measure. Given that the current study focuses on normative influence and not informational influence per se, these two items were removed from the construct for all subsequent analysis.

After removal of the informational influence items, a factor analysis of the remaining items showed a strong one-factor solution (eigenvalue = 1.72, 57.25% of variance explained), however, the Cronbach's alpha value for this scale was low (ca = .62), suggesting more items should be added to increase the reliability of this scale in the future.

Dependent Variables

Lastly, analysis was conducted to examine the structure of the dependent variables. As was discussed in the "measures" section (see above), dependent variables were organized around two main constructs: personal preference and intention-to-share. Therefore, in order to avoid analytical redundancy by running analysis for each of the seven individual variables separately, it was preferable to combine these variables into two main dependent variables representing these constructs.

To examine this, a correlation analysis was run with all seven dependent variables – because these variables refer to scores for each of the five songs presented to them, this involved five separate correlation analyses. The results showed that all dependent variables were strongly correlated with each other, for all songs (all possible correlations had $r > .48$, $p < .000$). A principal component analysis (PCA) was also conducted for the dependent variables for each song; results were highly suggestive of a single-component structure, with eigenvalues generally greater than 5.0 and variance explained values around 75% for the first component. Together, these results suggest that all dependent variables measured in this analysis are strongly related.

However, rather than combining all the dependent variables into a single score, the variables were combined into two separate scores, in reference to the structure discussed above. The resulting first item was composed of preference, willingness-to-download, and willingness-to-listen-again, which related to a person's private, personal preferences at the individual level. The second item computed was composed of both likelihood-to-recommend variables (recommend to a friend and to a relative), likelihood to re-post and to "like" the song on social media – these items were all seen to be more about self-expression or attempting to influence others. For the remainder of the analysis discussed here, the first variable will be referred to as "preference", while the second variable will be referred to as "intention to share".

Hypothesis 1

The first hypothesis is a manipulation check of the herding effect, regardless of any potential moderators and for now calculating the result regardless of genre. To calculate this, scores were created by combining the standardized dependent variable values for all songs, based on the social information condition. This created two variables: one representing the average scores of all songs presented with high social information, and another for low social information.

To test the hypothesis, t-tests were run to compare the values for each of the dependent variables. There was no significant difference for preference ($M_{highSI} = 0.0217$, $M_{lowSI} = -0.0242$; $t(82) = 0.548$, $p = .585$), nor for intention to share ($M_{highSI} = 0.0275$, $Ml_{owSI} = -0.0267$; $t(82) = 0.729$, $p = .468$), so we can retain the null hypothesis that there are no differences between the conditions. Therefore, it seems that the herding effect manipulation failed to occur, at least at this level of analysis.

Hypothesis 2

The next hypothesis aims to uncover whether there are differences in the effect based on type of music (the MUSIC factors). In order to determine this, ANCOVAs were used to test each of the two dependent variables separately and for each factor, with the condition of the video (high or low social information) being used as an independent (predictor) variable; additionally, covariates included in each model were: (1) age; (2) gender; and the frequency with which participants reported listening to (3) any music, (4) music on YouTube, and (5) new music. These were included as control variables since they are not part of the main research questions for this study.

Results of these ANCOVAs showed almost no variance as being accounted for by the predictor variables, with significant adjusted R-square values only being recorded for songs within the “M” and “U” factors; the results for these songs are presented in Table 4.

Table 4
ANCOVA Results

Factor	DV	Significant Variables	Parameter Estimates	Adj. R-Square
M	Preference	Gender[1]	.344 (F(1, 94) = 3.45, sig. = .066)	.020
	Intention to share	YouTube listen freq.	-.077 (F(1, 94) = 3.55, sig. = .063)	.074
		New music listen freq.	.082 (F(1, 94) = 5.01, sig. = .028)	
		Gender	.409 (F(1 ,94) = 6.41, sig. = .013)	
U	Preference	Gender	.401 (F(1, 94) = 3.72, sig. = .057)	-.013
	Intention to share	Gender	.480 (F(1, 94) = 7.32, sig. = .008)	.044

[1] “Gender” variable was coded as: 1.0 = male, 2.0 = female

As shown in Table 4, the only significant variables in these models are the control variables of gender and reported listening frequencies to YouTube and to new music. The results for YouTube show a negative parameter, suggesting that those who use YouTube to listen to music do not enjoy songs falling within the “M” factor, which tend to be mellow, relaxing, and slow. Additionally, it seems that those who listen to new music more frequently are more likely to share this song with others than those who avoid listening to new music.

For songs in both the “M” and “U” factor, gender was also a significant indicator of the dependent variable. It should be noted that in the analysis, gender was coded as 1 = male and 2 = female; therefore, these parameters can be interpreted as showing an increase in preference and intention to share if the participant is female. Given that factor “M” has characteristics that could be construed as more feminine (quiet, mellow, etc.), as does factor “U” (acoustic, non-aggressive, quiet, simple structure) (Rentfrow et al. 2011), these results are not surprising.

Apart from the results shown above, no variables were significant in the ANCOVA models for any other songs, and R-square values remain very low for these models, suggesting almost no variance in the dependent variables is being explained for songs other than factor “M”. Furthermore, despite the significant parameters discussed above, the experimental condition (level of social influence) was not significant in explaining the variance of either dependent variable for songs of any type. Therefore, we can retain the null hypotheses for H2a and H2b that there are no differences in the herding effect based on the types of music tested here without including other variables in the model.

Hypothesis 3

The final hypothesis asks if there are any potential moderators to the herding effect. Considering the previous analysis, findings here may shed light on whether these moderators are actually masking the herding effect itself, such that some participants' scores on the dependent variables are contrary to the expected effect, thereby cancelling out the scores of those who conform to the expected effect.

In order to answer the research questions in this hypothesis, regression analysis was utilized. Models were created for each moderator, which were then adapted for each MUSIC factor and each of the two dependent variables. Similar to the ANCOVA models conducted for the previous hypothesis, here some variables were included in the model in order to hold them constant throughout the analysis: these variables include: (1) age; (2) gender; and participants' reported frequencies that they listen to (3) any music, (4) music on Youtube, and (5) new music.

The results of these analyses will be presented in tables in the following sections, organized by moderator. Tables include variables which are significant or nearing marginal significance values (p values $< .10$); independent variables or interaction variables which are significant have been put into bold text.

Online Social Connectedness

The regression results for online social connectedness are shown in Table 5, below. Results for factors "S", "I", and "C" are similar to results found in the ANCOVA models used to examine Hypothesis 3 (see analysis above), so it seems that adding online social connectedness to the model does not uncover significant additional effects for these types of music.

However, factors "M" and "U" see some significant effects. Most importantly, marginally significant interaction effects (where $p < .10$) occur with the social influence condition (the herding effect), such that as online social connectedness increases, the effect of the condition strengthens for both dependent variables. In other words, it seems that people who feel connected with others in an online environment are more prone to herding effects – at least, for music that falls into factor "M". Therefore, H3a is partially supported.

Table 5
Regression Results for Moderator: Online Social Connectedness

DV	Significant Variables	Coefficients	R-square of Model	P-value of Model
Factor: M				
Preference	**Social info[1]*OnlineSC** YouTube listening freq. New music listening freq.	**0.199 (p = .097)** -0.152 (p = .025) 0.126 (p = .037)	.172	.207
Intention to share	**Social info** **Social info*OnlineSC** YouTube listening freq. New music listening freq.	**-0.834 (p = .054)** **0.171 (p = .089)** -0.139 (p = .014) 0.135 (p = .008)	.222	.068
Factor: U				
Preference	[None]	-	.090	.788
Intention to share	**Social info** Gender[2]	**-0.725 (p = .0995)** 0.410 (p = .085)	.153	.406
Factor: S				
Preference	[None]	-	.042	.936
Intention to share	[None]	-	.065	.794
Factor: I				
Preference	[None]	-	.074	.780
Intention to share	[None]	-	.023	.994
Factor: C				
Preference	[None]	-	.060	.843
Intention to share	[None]	-	.039	.955

[1] "Social info" variable was coded as: 1.0 = high social information, -1.0 = low social information
[2] "Gender" variable was coded as: 1.0 = male, 2.0 = female

The marginally-significant effect of the social information condition for factor "U" is an unexpected finding, since this variable's significance suggests that even after holding the interaction variable constant, there is still an additional effect of the condition. Furthermore, this relationship is negative, suggesting that participants rated the song *lower* when the song was presented with a strong social influence manipulation. Although this may seem to go against the herding effect, it could also suggest that identification with this song is not desired by this sample of participants. If this were the case, we would expect that a high social information condition would prompt the participants to rate that they do *not* like the song, in order to dissociate with those who may rate that they like the song (such as what is suggested by Larsen et al. 2009). Furthermore, this reverse effect of the social influence is only significant with participants' public behavioural intentions (the "intention to share" variable, which includes willingness to recommend to others, to share on social media, etc.) but not for their more private, personal ratings of preferences. This suggests a confirmation of this identification hypothesis, supporting Triandis' (1989) position of the possibility for differences based on a person's private and public "self", with their personal preferences incongruent with the public image of themselves they would like to project.

Finally, there are again significant results for YouTube and new music listening, which were included in the model as covariates based on their significance in the ANCOVAs run for H2. Discussion of the implications of these results occurred above, so will not be repeated here.

Self-Construal

Table 6
Regression Results for Moderator: Interdependent Self-Construal

DV	Significant Variables	Coefficients	R-square of Model	P-value of Model
Factor: M				
Preference	YouTube listening freq. New music listening freq.	-0.153 (p = .028) 0.109 (p = .075)	.136	.391
Intention to share	YouTube listening freq. New music listening freq.	-0.143 (p = .015) 0.125 (p = .016)	.187	.152
Factor: U				
Preference	[None]	-	.114	.646
Intention to share	[None]	-	.103	.712
Factor: S				
Preference	[None]	-	.033	.971
Intention to share	[None]	-	.064	.800
Factor: I				
Preference	[None]	-	.069	.817
Intention to share	[None]	-	.025	.991
Factor: C				
Preference	[None]	-	.066	.806
Intention to share	[None]	-	.052	.891

Tables 6 and 7 show the results of incorporating self-construal as a moderator. Based on the findings of the scale reliability analysis (as discussed above), and in conjunction with Singelis (1994), the inter- and independent aspects of this construct were analyzed separately.

Table 6 (above) displays the results of interdependent self-construal, showing that the addition of this moderator does not add any predictive power in helping to explain variance in the dependent variable. Therefore, H3b is not supported, so we can retain the null hypothesis that interdependent self-construal does not interact with the social information presented to help explain either dependent variable.

Table 7 (below) shows that this is not the case for the addition of independent self-construal as a moderator. Interestingly, though there continues to be no significant effects for factor “S”, the significant effects of moderation that existed for factors “M” and “U” for online social connectedness have not replicated here for self-construal, and instead factors “I” and “C” show significant effects.

Table 7
Regression Results for Moderator: Independent Self-Construal

DV	Significant Variables	Coefficients	R-square of Model	P-value of Model
Factor: M				
Preference	YouTube listening freq. New music listening freq.	-0.128 (p = .067) 0.110 (p = .069)	.161	.255
Intention to share	YouTube listening freq. New music listening freq.	-0.132 (p = .028) 0.122 (p = .019)	.184	.160
Factor: U				
Preference	[None]	-	.101	.723
Intention to share	[None]	-	.108	.679
Factor: S				
Preference	[None]	-	.050	.894
Intention to share	[None]	-	.065	.794
Factor: I				
Preference	SC_independence **Social info[1]*SC_independence**	-0.171 (p = .127) **-0.190 (p = .099)**	.127	.395
Intention to share	Social info*SC_independence	-0.157 (p = .123)	.065	.846
Factor: C				
Preference	**SC_independence**	**-0.218 (p = .070)**	.103	.509
Intention to share	Social info*SC_independence	0.167 (p = .136)	.077	.718

[1] “Social info” variable was coded as: 1.0 = high social information, -1.0 = low social information

Specifically, the results show a significant interaction effect between the social influence and participants’ level of independent self-construal. As level of independent self-construal increases, participants are less likely to report that they like the song if it is presented with high social information, and more likely to report liking the song if it is presented with low social information. This finding means that H3c is partially supported.

It could also be that gender effects exist here. The results for factors "M" and "U" in the ANCOVA analyses conducted for Hypothesis 2 show that gender effects occurred for more feminine songs; since songs in factors "I" and "C" are more masculine in style (loud, aggressive, distorted), it could be possible that a gender effect occurs here in an opposite fashion to what occurred for factors "M" and "U". Although not significant in the current model, this could be due to sample size – the topic of sample size will be discussed again in more detail in the discussion section, below.

Finally, it should be noted that the "significant" interactions discussed for this moderator are marginally significant, if the benchmark that is used for hypothesis testing is a significance value where $p < 0.05$. Cohen's (1994) article highlights the importance of interpreting statistical results as a whole, rather than completely discounting results that may fall below a traditional benchmark. Therefore, since these results are marginally significant ($p < .10$), and together form a trend, it was decided to include them in the discussion here. Additionally, because there is also a theoretical foundation for these results, it is expected that, should a larger sample size be obtained, these coefficients could rise to a level of traditional significance.

Need for Uniqueness

The results for including need for uniqueness as a moderator are presented in Table 8, below. Although the social information has no effect either on its own or in interaction with the moderator, need for uniqueness does seem to have a significant effect in predicting the dependent variable on its own, such that as the level of this trait increases, so do both dependent variables.

In other words, it seems that those who have a high need for uniqueness are more likely to share songs in factors "U" and "S" with others, and they also have a higher preference for songs in the "S" factor. Considering the general popularity of songs may provide clarification, since genres within factors "U" (country, bluegrass) and "S" (classical, jazz) (Rentfrow et al. 2011) tend to be less popular with younger people than with those who are older (Nielsen 2013; Bonneville-Roussy et al. 2013). Since the average age of this study is relatively young (mean age = 21.17 years old), this result could be explained by the fact that by rating preference for songs that are not typically popular with their age group, these participants are satisfying their need to be unique from their peers. This also helps to explain why the more public dependent variable (intention to share) has a stronger relationship with the dependent variables than does the more private dependent variable (personal preference).

Table 8
Regression Results for Moderator: Need for Uniqueness

DV	Significant Variables	Coefficients	R-square of Model	P-value of Model
Factor: M				
Preference	YouTube listening freq. New music listening freq.	-0.158 (p = .023) 0.109 (p = .068)	.141	.358
Intention to share	YouTube listening freq. New music listening freq.	-0.147 (p = .012) 0.122 (p = .016)	.198	.119
Factor: U				
Preference	[None]	-	.144	.455
Intention to share	**NeedforUni**	**0.173 (p = .052)**	.173	.306
Factor: S				
Preference	**NeedforUni**	**0.154 (p = .074)**	.076	.708
Intention to share	**NeedforUni**	**0.147 (p = .049)**	.117	.379
Factor: I				
Preference	[None]	-	.099	.595
Intention to share	[None]	-	.049	.926
Factor: C				
Preference	[None]	-	.055	.875
Intention to share	[None]	-	.046	.924

Therefore, although H3d is not supported because the moderator does not interact here with the social information, these results highlight that an individual's need for uniqueness does play a role in their music consumption habits.

Susceptibility to Normative Influence

Results for the final moderator, susceptibility to normative influence, are presented in Table 9, below. The results show that this variable seems to significantly predict both dependent variables for the "U" factor alone, though not in combination with the social influence condition. This result is surprising, since there is no theoretical foundation for susceptibility to normative influence to affect preference ratings or intention to share on its own. Due to the lack of a significant interaction effect, H3e is not supported.

Table 9
Regression Results for Moderator: Susceptibility to Normative Influence

DV	Significant Variables	Coefficients	R-square of Model	P-value of Model
Factor: M				
Preference	SuscepttoNI	0.145 (p = .144)	.193	.134
	YouTube listening freq.	-0.161 (p = .016)		
	New music listening freq.	0.114 (p = .050)		
Intention to share	SuscepttoNI	0.132 (p = .112)	.239	.046
	YouTube listening freq.	-0.147 (p = .009)		
	New music listening freq.	0.125 (p = .011)		
	Gender[2]	0.347 (p = .099)		
Factor: U				
Preference	**SuscepttoNI**	**0.274 (p = .042)**	.166	.338
	Gender	0.546 (p = .076)		
Intention to share	**SuscepttoNI**	**0.189 (p = .075)**	.156	.388
	Gender	0.460 (p = .061)		
Factor: S				
Preference	**Social info**[1]	**-0.447 (p = .103)**	.051	.889
Intention to share	**Social info**	**-0.414 (p = .080)**	.084	.639
Factor: I				
Preference	[None]	-	.077	.762
Intention to share	[None]	-	.048	.930
Factor: C				
Preference	[None]	-	.052	.894
Intention to share	[None]	-	.059	.848

[1] "Social info" variable was coded as: 1.0 = high social information, -1.0 = low social information
[2] "Gender" variable was coded as: 1.0 = male, 2.0 = female

Gender appears in this model as marginally significant for factors "M" and "U"; this is not surprising, given the discussion of gender that was included above. Not all variables listed above show conventional significance values ($p < .05$); however, these variables are included because their p-values are approaching marginal significance (assuming $p < .10$). Additionally, it appears that when these variables are held constant in the model, marginal effects for the social influence condition appear for the "S" condition.

DISCUSSION

Discussion of Findings

The herding effect has been shown to be a strong example of the power of social influence. Past studies examining this effect have examined its reliability, the extent of the effect, and its generalizability to a variety of situations. However, researchers have not yet examined whether there are any potential moderators to this effect, such as personality traits that could affect consumers' likelihood of being affected by this social influence effect. Additionally, studies on herding effects that examine its role in music consumption have generally avoided any discussion of differences that could occur between different types of music, and have only looked at the effects it has on product choice, rather than examining the effect it has on the consumption experience. Therefore, the purpose of this study is to examine these questions in the context of online music consumption.

Studies on the herding effect have generally shown a strong effect to occur. Despite this, in this study the basic effect of the social influence manipulation was not significant. Further analysis looking into whether any differences existed for this effect based on type of music were also not significant. These results appears to go against previous research in this area; however, it should be noted that these previous studies often involved much larger samples (as mentioned previously, Salganik et al.'s (2006) study involved nearly 14,000 participants), and as such, the sample used in this study may be too small for these overarching effects to appear.

However, differences begin to appear regarding the type of music once analysis of potential personality moderators begins. Online social connectedness was found to be significant for music in the "M" factor, such that people who feel more socially connected are more prone to herding effects.

It is not clear at this point why this effect is only significant for one type of music and not others. Nonetheless, for the "M" factor this is a logical finding, suggesting that there exists a facet of the population who generally pays attention to others' preferences and feels that they are connected with others in this way. It may also suggest that the herding effect is less likely to be as powerful a social influence tool for those who are lower in social connectedness. Given the herding effect manipulation, a plausible null hypothesis for this construct would assume that those high in social connectedness may pay attention to the high popularity of the songs, but only as a means to fit in and "feel connected" with others; if this were the case, we would expect the interaction to be significant for the public dependent variable (intention to share), but not the private one (personal preference). However, the fact that this relationship was at least marginally significant for both the private and public dependent variables indicates that the herding effect may genuinely affect preferences for those high in online social connectedness, such that they view high popularity of the song an indication of its quality; this influences their opinions, leading them to subsequently report higher preference for the song.

Findings for self-construal support the structure presented by Singelis (1994), in which participants' inter- and independent scores are not correlated. While interdependence was not found to act as a moderator to the herding effect, independence was found to have significant interactions with the effect. These results show that those who see themselves as highly independent tend to actively go "against-the-trend", reporting to like the song less if they see that many other people report liking the song. Conceptually, this is in line with the basic concept of an independent self-construal: those high in independence place emphasis on the self and on making unique, independent decisions (Singelis 1994; Markus & Kitayama 1991). Therefore, it is not surprising that a strong social influence effect will prompt them to make decisions that are contrary to those of the general population, since doing so allows them to assert their independence. The fact that this interaction only exists for songs within factors "I" and "C" is likely due to the fact that these genres are popular with young people (Nielsen 2013; Bonneville-Roussy et al. 2013); because these songs are popular with their peers, it is not surprising that participants choose these songs to prove their independence, since the contrast to the preferences of others will be stronger and more obvious here than with other types of music.

Given this finding for independent self-construal, the fact that the need for uniqueness construct is significant on its own and does not yield a similar, significant interaction with the social information effect is surprising. However, an alternative explanation is given for the finding that need for uniqueness is significant on its own in predicting participants' intention to share (and, to a lesser extent, their preference), since it seems that by recommending songs in styles that are not generally popular with their peers, these individuals are satisfying their need to be unique. If this is the case, we can then assume that the generally-perceived music-style popularity among peers is acting as a proxy for the lack of a significant social information effect. Finally, it seems that a consumer's susceptibility to normative influence does not moderate the herding effect.

Although they were not originally hypothesized to be significant predictors, some covariates were shown to have an effect in predicting participants' reported preferences and behavioural intentions. Findings for the frequency that participants listen to music on YouTube suggest that those who use this online service more tend to have more negative ratings of songs. This could be due to the lack of quality control that exists for music on this site, since any individual can upload music to YouTube; the lack of a gatekeeper on the site to tell people what music to listen to (Waldfogel 2012) could mean that these participants have to sort through a large amount of music in order to find songs of high perceived quality, leading them to adopt a more pessimistic, jaded view of new music when it is presented to them. On the other hand, those who report listening to new music more frequently tend to report higher preferences for new songs, suggesting they may be more open to new musical experiences in general. A future extention of this finding could aim to see whether this is effect is related to the more general Big Five personality trait of Openness to Experience; if so, this could act as another personality moderator to the herding effect.

Additionally, gender was occasionally found to have a significant effect. Given the masculine and feminine connotations associated with some types of music, these results are not surprising; however, future research should be aware of this, and should take these gender differences into account when choosing potential musical stimuli.

Implications

Implications for Researchers

This research follows a line of studies which look at social influence and herding effects in cultural markets (Salganik et al. 2006, 2008; Chen 2008; Berns et al. 2010; Maecker et al. 2013, etc.). Though findings here were limited in the extent to which they mirror results from previous studies (e.g., the finding that there was no overall effect without including moderators in the model), the significant findings that were found in this research still support past literature, further emphasizing the importance of studying social influence in cultural markets.

This study also provides more clarity regarding the outcomes of the herding effect. While most past studies have looked only at one outcome at a time, such as product choice or acquisition (Hanson & Putler 1996; Salganik et al. 2006) or behavioural outcomes such as re-tweeting (Langley et al. 2014), this study examines two separate dependent variables in the same setting, allowing for a compare-and-contrast of the outcomes in order to better understand the nature of the herding effect. Specifically, outcome variables were divided into a private-versus-public dichotomy; given that the herding effect is a social influence effect, this provides valuable insight into the depth of the effect – that is, whether participants view the herd as something that must simply be followed in order to “fit in”, or whether they view the decisions of the herd to be due to expert knowledge (Moussaid et al. 2013), thereby adjusting their preferences accordingly. Results do indeed show this to be true for the online social connectedness moderator: for this variable it seems that the herding effect is inspiring actual changes in personal preferences for respondents high in this trait. In some cases this is not true: for example, while those with a highly independent self-construal use this to their advantage, rating that they are less likely to share songs that are shown with high social information (perhaps as a way of showing that they are unique and different), their personal, private preferences about the songs are not affected.

More generally, this study helps to answer questions about potential moderators of the herding effect. Some personality traits were found to be significant in this regard, such as online social connectedness and an individual’s self-construal, suggesting that studies in the future should consider this in their research designs. While the type of music does not seem to moderate the herding effect on its own, some types of music do appear to interact with some moderators, such as those mentioned above. Overall, more research is needed to confirm the role that music type plays in moderating the effect.

Apart from the implications on our understanding of the herding effect, some particular findings are of note for the individual constructs used in conjunction with the effect here. For one, findings for online social connectedness help further our understanding of this trait: use of the online version of the social connectedness construct has been limited in research thus far (see Grieve et al. 2013), and the findings presented here which find a significant relationship with the well-founded social information manipulation (the herding effect) provide more validity for this construct as a useful social personality trait.

Managerial Implications

Marketing managers can use the findings here to help determine whether a marketing strategy that utilizes the herding effect (for example, attempting to create a “viral video”) will be successful, depending on the type of music they are attempting to market. Interesting findings suggest that participants may use their sharing of music and their reporting of their music preferences in order to attempt to be unique. This may work in the managers' favour: this study found that those who have a high need to be unique were likely significantly more likely to report an intention to share music that is not generally popular with their age range (songs in the "U" and "S" categories, which includes genres of country and bluegrass, and classical and jazz music, respectively) as a way of appearing different and distinct from others. This finding was significant regardless of the social information presented, suggesting that these consumers may be ideal candidates to recruit as initial fans as they will not be negatively affected by the low level of social support a song has (e.g., the low number of "likes" a music video has) at the beginning of a marketing campaign.

However, these findings may also work against managers for some types of music: those who had a highly independent self-construal had significantly lower preference ratings and were less likely to share songs which were in genres such as rock and heavy metal, and rap and electronica (factors "I" and "C", respectively). This seems to be due to the fact that these music types are generally popular among their peers, and their need to appear independent of others leads them to report not liking these generally-liked songs. Therefore, these participants would likely not be responsive to a marketing campaign for these types of songs, regardless of their personal preferences, since their need to appear independent does allow them to express music preferences that are common among their peers.

These findings may also have implications outside of the music industry, and the more general findings of personality traits that act as moderators to the herding effect can be taken into consideration for anyone attempting to use social influence in their marketing strategy. As social influence mechanisms are pervasive in marketing strategies for consumer goods and services today, these findings are likely applicable to many industries outside of just music or other cultural goods.

Limitations and Future Research

While maintaining ecological validity guided many decisions in this study, including the choice of the stimuli presentation method, many steps were also taken to control for internal validity. The choice of an in-person data collection method allowed for the environment to be controlled: network speed was consistent across computers, avoiding any influences this may have on playback quality, and the equipment used – including computer type, operating system, browser version, and headphone type and quality – was identical for all participants, allowing for confidence that environmental factors were not influencing responses. Additionally, the experimenter was able to monitor participants to be sure that they actually experienced the manipulation and the stimuli (i.e., that they listened to the song and paid attention to the screen at this point in the survey).

However, while controlling for internal validity through these methods was advantageous in allowing further observation of the data collection and ensuring higher quality of the data overall, these choices came at the cost of external validity by artificially placing participants in a new-music consumption scenario in an environment which they may not have been comfortable in – for example, by using computers and headphones they were not originally familiar with. Additionally, this data collection method meant that only a limited number of participants could be involved in the study, which limited the number of valid responses; it appears that this may have affected the significance of the analysis that followed.

Because of the limited size of the sample, some questions remain about the analysis discussed in this study. The number and nature of significant results could change given an increase in sample size – in the least, some relationships that could exist, given past literature and the results found here, may become significant given a larger sample size. Future research using a larger sample of participants can help to clarify results reported here, such as the finding that independent self-construal has a significant interaction effect with social information due to participants' desire to be unique, while the need for uniqueness variable does not have a similarly significant interaction.

Another limitation of this study is the limited age range of the participants, who were all undergraduate students. Findings presented here which relate to peer groups and musical preferences by age are hypothesized based on previous literature (for example, Bonneville-Roussy et al. 2013), but are not able to be empirically tested in this study because of the limited age range. Future research which utilizes a wider age range could help to confirm these points, perhaps providing more insight into these hypothesis than what was considered here.

Additionally, although age was included as a covariate in the models, it was not significant in any model; this could very easily be due to the lack of variance within the age variable. Further, normative age trends in music preferences have been shown to exist

(Bonneville-Roussy et al. 2013), so an interesting future research area could be to examine whether any of the findings here are subject to changes based on age.

Finally, some doubt may exist regarding the social information manipulation. Steps were taken to attempt to confirm that the manipulation occurred (i.e., that participants saw and interpreted the social information presented with each song), including the presentation of the social information in a list before the first song. However, the setup of the social information at the same time as the stimuli may have led to a general disregard of the social information, since this decision heuristic was not needed if they were simultaneously experiencing the song. This is a differentiation of the current study over past studies (such as Salganik et al. 2006 or Hanson and Putler 1996) which analyzed product choice; in these past studies, participants were asked to choose a product based on social information *before* experiencing the product. While the current study's setup increases ecological validity by more closely replicating a consumption experience consumers are likely to experience in real-life, the results here are not definitive in proving whether the herding effect applies to product experience in the same way it applies to product choice. Should the aforementioned future research suggestions (regarding an increase in sample size and a focus on age heterogeneity) be insufficient in achieving the same effect, it may be possible to design a study in which both of these designs are used in conjunction. Doing so would provide a clear way to determine whether the effect's strength is the same when applied to product choice as it is when applied to product experience.

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APPENDICES

Appendix A
List of Personality Trait Measures Used

All scales evaluated on 7-point scales, with anchors at: 0 = "Not at all", 7 = "To a great extent"

Online Social Connectedness
Source: Grieve et al. (2013); adapted from Lee et al. (2001)

1. I feel close to people online
2. I fit in well when I'm new to an online community
3. *I feel like an outsider when online
4. I am able to relate to my peers online
5. *I feel disconnected from the online world

*Indicates reverse-coded items

Self-Construal
Source: Singelis (1994)

Interdependent items:
1. It is important for me to maintain harmony within my group
2. I will sacrifice my self-interest for the benefit of the group I am in
3. I often have the feeling that my relationships with others are more important than my own accomplishments
4. It is important to me to respect decisions made by the group

Independent items:
1. Speaking up during a class is not a problem for me
2. I prefer to be direct and forthright when dealing with people I've just met
3. I enjoy being unique and different from others in many respects
4. My personal identity independent of others, is very important to me

Need for Uniqueness Scale (Avoidance of Similarity Dimension)
Source: Tian et al. (2001); adapted here to a music consumption environment

1. When music I listen to becomes popular among the general population, I begin using it less
2. *I often listen to music that I know is listened to by the general population
3. As a rule, I dislike music that is customarily purchased by everyone
4. The more a piece of music is listened to by the general population, the less interested I am in listening to it

*Indicates reverse-coded items

Susceptibility to Normative and Informational Influence Scales
Source: Bearden et al. (1989)

Normative items:

1. I rarely listen to new music until I am sure my friends approve of it
2. It is important that others like the music I listen to
3. I achieve a sense of belonging by listening the same music that others listen to

Informational items:

1. To make sure I listen to the right music, I often observe what others are listening to
2. If I have little experience with a musical artist or band, I often ask my friends about them