Turning Attention:

The certifying role of a Dutch television show

Measuring The 'De Wereld Draait Door-Effect'

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Abstract

This study researches the certifying role of Dutch TV-show De Wereld Draait Door. As creative goods like music are experience goods, it means that consumers do not know the value of the product or service before purchasing it. Therefore, consumers retrieve information in order to lower uncertainty about a product or service. An example of how consumers do this is herd behaviour, where they base their decision on what others are doing. Another way of lowering uncertainty is by listening to a certifier; someone who provides the consumer with information about the good or service. Digitalisation and Web 2.0 make that the pile of goods to choose from is so big, the need for certifiers increases, while the need for gatekeepers decreases due to the concept of prosumation, which in turn is shifting boundaries between 'professional suppliers' and 'amateurs' or 'consumers'. As De Wereld Draait Door is an example of a certifier within the music industry, the literature leads us to the following research question:Does De Wereld Draait Door has a certifying role for artists and/or bands performing in the show? If so, what type of attention does the show generate for the musicians?with the next follow-up question: Are there any other (musical and/or aesthetical) characteristics influencing the type of attention for the artist or band?This research investigates whether certifiers really have a more important role like the literature assumes, by measuring the impact of De Wereld Draait Door on the number of Google Searches, the number of views on YouTube and the number of subscribers on YouTube. In addition it looks at whether there are musical and aesthetical characteristics which influence the type and depth of the attention generated by De Wereld Draait Door. In order to do this, a content analysis is conducted. Our main findings consist of that we can talk about a 'De Wereld Draait Door – effect', as the show does generate attention in terms of Google Searches and YouTube subscribers. The results of correlations between our independent variables account for us setting up a musician profile for whom De Wereld Draait Door creates the biggest increase in attention. As we have shown that certifiers really do play a big role, it could have a big influence on the democratisation of the music industry. Shows like De Wereld Draait Door have the power to break through the power of the traditional players in the industry, such as record labels.

KEYWORDS: *Certifiers, Gatekeepers, Taste, Attention, Music Industry, Visual Aesthetics*

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Introduction

The studio is quiet. All eyes are on Dutch rapper Ali B waiting for him to start a song which he performs with singer Ruben Annink. As Ali starts rapping about his children, tears are rolling from his eyes over his cheeks, and the whole audience holds their breaths and tear up with him.

On May 22nd 2015 Ali B performed this song on Dutch television show *De Wereld Draait Door*. On the same day the term 'Ali B' had more than twice as much hits on Google and within a few hours the song was viewed more than 150.000 times on YouTube (GoogleTrends.com & socialblade.com).

When it comes to buying or 'consuming' music, we can say that musical and aesthetical characteristics of a song influence the buying decision of the consumer. Bruner (1990) and Kellaris & Rice (1990) conclude that the tempo, pitch and volume of the song is of great influence in consumer liking, which in turn can influence the buying process. In addition, Bloch, Brunel & Arnold (2003) state that consumers increasingly make brand choices based on the aesthetic value and distinctiveness of visual design. However, when people have to make a buying decision, they are not only influenced by musical and visual aesthetics.

Music is an experience good, as most creative goods are. This means that consumers cannot be sure of the value of such a good, without purchasing that good; they only know the value after purchasing (Caves, 2000). Trying to lower the uncertainty about the value of the good or service, consumers invest in getting information about this good or service. Every consumer's hunch about this good or service has a chance to be correct, but it is no sure thing (Caves, 2000). Instead of just relying on his/her own hunch, the consumer looks at what everybody else is doing, also called herd behaviour, which declines the uncertainty about the certain product or service (Caves, 2000).

Certifiers are people who can lower uncertainty for the consumers, leading consumers of creative goods to rely on them. Certifiers lower uncertainty by providing more information about the good or service, information which cannot be expected from the good's creator or seller. Gatekeepers, however, decide whether the prospective value of the artist's creative input warrants the cost of humdrum inputs needed to place it before final buyers (Caves, 2000). Thus, if gatekeepers decide not to place a creative product or service before final buyers, the certifiers' expertise is not needed, as the product is not accessible to the public.

Nowadays, digital technologies are in the very early stages of their development. Their long run impact on the creative sector will be complex, with a big range of unpredictable outcomes (Towse & Handke, 2013). Consumers have access to a range of technologies which were unthinkable a few decades ago (Towse & Handke, 2013). These new technologies allow consumers to search for information about a certain good or service on the world wide web, lowering their search costs. Web 2.0 (e.g. Social Media) makes it possible for consumers to overload each other with information about their experiences with a certain product, making product information easily available, but increasing the amount of goods or services to choose from.

Additionally, this Web 2.0 makes it easier for suppliers to market themselves, without the help of intermediaries such as gatekeepers. As an example, musicians can now put their music on YouTube, directly addressing their target audience, without going through the process of gatekeeping. Thus, there are opportunities for independent artists, as the music market has experienced a shift in demand, and where supply is “fragmenting into a multiplicity of sub-genres and across a wider set of bands” (Weeds, 2011). It is assumed that the focus nowadays lies more on the niches instead of the hit-artists. However, the growing amount of goods which consumers can choose from, assumes that there is a growing need for certifiers and critics, as these consumers need more and more information to make a ‘rational’ choice between all those goods that are now available.

The literature suggest that the process of digitization implies that the roles of gatekeepers and certifiers is changing. The role of gatekeepers seems more and more unnecessary, while the role of certifiers is increasing. This can have great influences on the processes of bringing creative goods to the market and is something that is interesting on the fields of marketing, economics and culture, while there are no published researches about this subject yet.

Certifiers influence consumer’s buying behaviour in the way that they lower risk and uncertainty, which in turn lowers search costs for consumers. Cunningham, Gerlach, Harper & Yong (2005) describe the consumer buying process as a five-stage linear process: (1) need recognition, (2) information search, (3) alternatives evaluation, (4) purchase decision, and (5) post-purchase behaviour. This process assumes that each step needs a deeper form of attention, which eventually results in buying the product or service.

An example of a certifier for the music industry are television shows, especially primetime, non-commercial daily shows. A television show which fits this description within the Dutch television industry is *De Wereld Draait Door*, or directly translated into English:

‘The World Keeps Turning’. This show offers a stage for different artists every day, giving them the opportunity to play one of their songs for 1 minute. Some artists get to play more songs as well, but all play the famous ‘1 minute’.

Interesting to see is if *De Wereld Draait Door* really has a certifying role for Dutch as well as international artists and if they do, to what extent this role leads to (the depth of) attention for the artists or bands performing in *De Wereld Draait Door.* Is the role of a certifier really that important? Musical as well as aesthetical characteristics also have to be taken into account when researching the amount of attention leading to success of the artist or band. Therefore, we propose the following research question:

Does De Wereld Draait Door has a certifying role for artists and/or bands performing in the show? If so, what type of attention does the show generate for the musicians?

Following whether there is a DWDD-effect, it is interesting to see if there are any other variables influencing this (type of) attention. Therefore, we adopt the next follow-up question:

Are there any other (musical and/or aesthetical) characteristics influencing the type of attention for the artist or band?

We address this question by means of a quantitative study based on the number of Google Searches, the number of Views on YouTube and the number of Subscribers on YouTube as our dependent variables. We will look if we can speak of a ‘*De Wereld Draait Door – effect’* in which the show plays a significant role in creating attention for artists. The independent variables are musical, aesthetical and control variables, for which we will conduct a regression analysis to see whether there are variables influencing the attention an artist receives by performing on *De Wereld Draait Door.* Correlations between the dependent and independent (between and cross) will be explored and the results of these tests will be discussed. In the end, conclusions based on the results of our research will be drawn, after which recommendations for further research will be given.

Literature review

Risk & the consumer buying process

Uncertainty about cultural products on the market is high, due to, amongst other things, asymmetrical information (Caves, 2000). Thus, each purchase decision by a consumer involves risk when the consequences connected with the decision are uncertain and some results are more desirable than others (Cunningham, Gerlach, Harper & Yong, 2005). Perceived risk is usually measured as a construct with multiple dimensions: physical loss, financial loss, psychological loss, time loss, performance risk, and social risk (Roselius, 1971). It is said that when this perceived risk falls below the consumer's acceptance value, it has little to no effect on the intended behaviour and it is mostly ignored (Greatorex and Mitchell, 1993). Moreover, an extremely high level of perceived risk can cause a consumer to postpone or avoid a purchase entirely. Usually, perceived risk is conceptualized as a typical influence that is addressed during the early stages of the consumer buying process (Zeithaml and Bitner, 2003; Cox, 1967; Dowling and Staelin, 1994; Murray, 1991; Murray and Schlater, 1990, in: Cunningham et al., 2005).

The consumer buying process is commonly described as a five-stage linear process (Blackwell et al., 2003; Hawkins et al., 2003, in: Cunningham et al., 2005): (1) need recognition, (2) information search, (3) alternatives evaluation, (4) purchase decision, and (5) post-purchase behaviour. In the first stage, consumers first perceive risk when they recognize the need for a product or service. In the presence of uncomfortable levels of perceived risk, consumers apply risk reduction strategies during the second and third stages, such as reliance on personal recommendations (Cunningham, 1967; Midgley, 1983; Perry and Hamm, 1969, in: Cunningham et al., 2005), seeking additional information about a product or service (Beatty and Smith, 1987; Cox, 1967; Lutz and Reilley, 1973, in: Cunningham et al., 2005), a preference for national brands (Bauer, 1960; Locander and Herman, 1979; Lutz and Reilley, 1973, in: Cunningham et al., 2005), and the security of warranties (Bettman, 1973; Cox, 1967; Dowling and Staelin, 1994, in: Cunningham et al., 2005).

Thus, in the case of the music industry, we have seen that branding is harder, meaning that liking one song of a particular band does not necessarily mean that someone will like all following songs too. There is in this case thus no security of warranties or reducing uncertainty by branding. What is left is that consumers rely on personal recommendations and that they will seek additional information about a certain band or musician, which leads to reducing the risk (which in this case is similar to and complementary of uncertainty). Stage one might in the case of television-shows which function as certifiers be less visible, as people watch this show every day, leaving the need or the knowledge of needing a product less visible or important. People might ‘stumble’ upon a music recommendation, without knowing they needed it. But then immediately stage two and three proceed (after they realised they needed something without knowing it beforehand). The consumer’s search costs are directly lowered, as the certifying function of the television show is an immediate example of a recommendation.

However, what people might do is search for more information about this particular band or musician on the internet, followed by (if risk is lowered) a possible purchase (in the case of music, a cd, download stream or I-Tunes song for example). But, before consumers make the decision to buy a product, a lot of considerations and actions precede this buying decision. We can state that there are different levels, types or even stages of attention to a certain product, all the way up to (one of the) final stage(s): buying the product.

In this research we use three stages of attention, starting with the most ‘superficial’ type of attention: searching for the band or musician a consumer heard and saw on DWDD on Google. A more deeper form of attention is actually listening and watching music videos by this band or musician or YouTube. The deepest level of attention in this case is than when the consumer subscribes themselves to the YouTube page of this musician or band, which usually means the consumer wants to keep following what this artist does, with a sincere amount of interest in the band or musician. The consumer’s attention in this case leads to success for the artist.

Our question than is if there is an effect of television shows on the attention a musician gets, and if yes, to what extent does the show affect each of the three forms of attention?

Increasing need for certifiers

Most, if not all cultural products are experience goods, or at least they have got experience good attributes (Caves, 2000). Two of these attributes are high search costs, and the fact that experience goods’ attributes can only be evaluated after it has been consumed (Nelson, 1970, p. 312; Hutter, 2011, p. 211). Music for example is also an experience good, meaning the consumers do not know anything about the quality of a song before they have listened to the song.

By gaining as much information as possible about the product, consumers try to deal with this product uncertainty with as low as possible search costs (Caves, 2000, p. 179). Herd behaviour, informational cascades or band-wagon effects, assure that consumers are able to lower product uncertainty. In these cases, consumers prefer to do what other people do, especially in areas where the quality of goods is uncertain (Kretschmer, Klimis & Choi, 1999, p. S63). There are different types of quality signals to mitigate problems with quality uncertainty, such as: brands and reputation, charts and rankings and professional reviews and recommendations, to name just a few (Caves, 2000; Akerlof, 1970).

The people behind these rankings and reviews are called certifiers; people who present themselves as independent and experienced evaluators of creative goods (Caves, 2000). Certifiers have the advantage to be neutral and objective. In the first place, a certifier can among other things provide a description of the good or service, something that could not be expected from the good's creator, as their incentive is to 'puff' the product, with a commercial incentive (Caves, 2000). Secondly, a critic or certifier internalizes prospective consumers tastes and makes an attempt to prejudge the creative good's appeal (Caves, 2000). Certifiers then lower consumers' search costs.

A different type of quality signal is branding. Nelson (1970) states the following about brands: *"its price and quality can be combined to give the consumer posterior estimates of the utility of its purchase. Prior to using the brand, all the consumer knows is its price"* (p. 313). Nelson (1970) states that due to their experience, consumers can determine their brand preference. When re-buying a product of the same brand, consumers lower their search costs compared to when they would buy a new unfamiliar product. The fact that the consumer already has had an experience with the brand (which resulted in either a good or bad experience) makes that the search costs are lowered. Brands than have an established function, lowering product uncertainty for the consumer (Nelson, 1970). This again implies that when consumers do not have a lot of pre-purchase information, the brands, or incumbents, benefit because the consumer is not very likely to try something new, if he or she learnt from experience that that one product by that certain brand was good (enough).

Compared to other information sources, certifiers may offer advantages such as expert status: having large stocks of knowledge capital, and absence of bias toward or against the goods of particular suppliers (Caves, 2000). The amount of authority that these critics have depends on the quality of other sources of information used by the consumer (Caves, 2000).

However, the services of these certifiers have high costs, as their knowledge and taste capital is a humdrum asset that must be compensated. Additionally, their neutrality could be at risk of corruption by producers. Furthermore, certification comes from prizes and awards, which recognize the artistic achievement and may also sign quality to consumers. But here also, consumers face the credibility of the received signals (Caves, 2000).

In comparison with certifiers, gatekeepers decide whether the prospective value of the artist's creative input warrants the cost of humdrum inputs needed to place it before final buyers (Caves, 2000). They play a critical role in determining what creative products eventually reach audiences (Foster, Borgatti & Jones, 2011). Gatekeepers are brokers who mediate between artists and audiences. However, cultural production research contains different definitions of the gatekeeper role: as co-producer, tastemaker and as selector (Foster, Borgatti & Jones, 2011). Gatekeepers as co-producers steer artists and products through the production process, operating almost as artists themselves by shaping the content of a cultural product (Peterson & Berger, 1971). According to Gould and Fernandez (1989, p. 92) ''gatekeeping occurs when an actor selectively grants outsiders access to members of his or her own group.''

Each creative sector has its set of intermediaries who select artists. These selection choices are based on their own mixture of motives (Caves, 2000), which in turn leads to multiple definitions of gatekeepers. sometimes also linking a certifying or tastemaking role to gatekeepers (Foster, Borgatti & Jones, 2011). Gatekeepers base their selections not only on the artist's talents, but also on his or her personal qualities, which are important for collaborating with other artistic and humdrum inputs (Caves, 2000). For this research the definitions of certifiers as well as gatekeepers mentioned above will be used. The possible certifying or tastemaking role of gatekeepers will be left out of this consideration, focusing on their selectivity and decisions on what creative products will reach the consumers. → onder de definitie.

Music & taste

When looking at the music and record label industry, we can say that music is an experience good; consumers do not know the utility of the song, until they have listened to the song (Caves, 2000). As stated earlier, people try to reduce uncertainty of experience goods by getting as much pre-purchase information as possible. In addition, we have seen that branding also often reduces quality uncertainty, but does this account for the music industry as well? As every new song, may it be by the same artist, is different from the last one. Consuming new songs assumingly cannot be compared with picking Coca-Cola because consumers know they like that brand; knowing they like the artist does not necessarily mean they will like every next song the artist produces.

If quality uncertainty is not necessarily lowered by the existence of brands for the consumer, or in the case of the music industry, a certain artist (or record label), consumers might rely on their taste for a certain music style or genre. Tastes are often assumed to change as a result of consuming certain "addictive" goods (Becker & Stigler, 1977). Consuming the product more than once in a certain period is likely to increase the desire for that good, or in economic terms; their marginal utility is said to rise over time because tastes shift in their favour, also called rational addiction (Becker & Stigler, 1977). Music appreciation depends on the time spent on music, the training and other human capital conducive to music appreciation. As stated by Becker & Stigler (1977): "An increase in this music capital increases the productivity of time spent listening to or devoted in other ways to music" (p.78). In other words, the more good music someone hears, the more appreciation there is for this type of music, lowering quality uncertainty. Thus, it can be said that taste and rational addiction can lower quality uncertainty.

Digitization & its effect on gatekeepers

Due to digitization, information about products is widely available on the internet, also causing product uncertainty to decline (Towse & Handke, 2013). As consumers can now rely on the information about new products available online and for less money, it seems that brands do not have an as big advantage as before. Search costs are lowered too, as now all information is literally available at the tip of your fingers. Relatively all former used quality signals become cheaper or less important due to digitization, but they might still cause a buzz. This process started by digitization might resemble the process of creative destruction, in which innovative suppliers generate productivity increases or new superior products, gain competitive advantages and win over market share at the expense of more conservative suppliers, which leads to productivity increases throughout the industry (Schumpeter, 1942 in; Handke, 2010). The internet then causes other suppliers to gain competitive advantages over incumbents by lowering search costs and uncertainty, while the amount of product information is increased.

With digitization came web 2.0 or Social Media. Web 2.0 has had and still has a substantial effect on consumer behaviour, as it has also contributed to an unprecedented customer empowerment. The consequences are far reaching, affecting not only the area of technology development but also the domains of business strategy and marketing (Constantinides & Fountain, 2007). Constantinides & Fountain (2007) suggest that "Web 2.0 or Social Media is affecting the way people communicate, make decisions, socialise, learn, entertain themselves, interact with each other or even do their shopping" (p. 232).

Also suggested is that Web 2.0, next to changing peoples' individual and group behaviour, has had an effect on the power structures in the marketplace as well, causing a great migration of market power from producers or merchants towards customers. The main reason for this is that today's online consumer has access to a previously unknown reservoir of information and knowledge as well as unlimited choice, available at the click of the computer mouse (Constantinides & Fountain, 2007). Thus, another way for consumers to reduce quality uncertainty regarding music, is to spend their time browsing clips on YouTube. Due to digitization, cultural participation is enriched and consumers turn into prosumers, which in turn is shifting boundaries between 'professional suppliers' and 'amateurs' or 'consumers' (Towse & Handke, 2013).

We use the term Web 2.0 since about 2005, but the subject is already controversial. This controversy comes from the fact that Web 2.0 applications are for the bigger part based on content generated by users often being anonymous and lacking qualitative credentials and opinions (Constantinides & Fountain, 2007). Web 2.0 differs in that way from previous internet applications in that: the user now has an essential role as contributor, which can be seen as a new marketing parameter, instigating a shift of market power from producers to consumers and from traditional mass media to new personalised ones (Constantinides & Fountain, 2007). Web 2.0 presents businesses both with new challenges and opportunities for getting and staying in touch with their markets, learning about the needs and opinions of their customers as well as interacting with them in a direct and personalised way (Constantinides & Fountain, 2007). The user is a vital factor for all categories of Web 2.0 applications, not only as a consumer but mainly as a content contributor or content creator. The term User-Generated Content (UGC) is often used to underline this characteristic of Web 2.0 application categories (Constantinides & Fountain, 2007).

Consumers nowadays hold a greater share of the market power. However, before digitization, the producers, or in the music industry record labels and publishers, had this power. They got their power primarily from their role as gatekeepers, a role which enabled them to decide whether the prospective value of the artist's creative input warrants the cost of humdrum inputs needed to place it before final buyers (Caves, 2000). As gatekeepers, they played a critical role in determining what creative products eventually reach audiences (Foster, Borgatti & Jones, 2011). Gatekeepers are brokers who mediate between artists and audiences, meaning that over the twentieth century, the publisher's contribution to a song's success has greatly diminished. The shift on not only the consumer side, but also the supplier side, accounted for the fact that artists could now take on the role that their gatekeepers had before, leaving mere bookkeeping tasks for the publishers (Caves, 2000, p. 310).

Bockstedt et al. (2005) argue that in the music industry: "New digital recording and distribution technologies present opportunities for artists to adopt a do-it-yourself approach. Before, artists depended on labels for access to production and distribution capabilities. With digital technologies and the Internet, artists can produce, record and distribute music without the help from record labels" (p. 6). With the do-it-yourself approach, independent artists are able to make their musical product commercially viable without the interference of gatekeepers like record labels. Having stated that artists should be able to make their product available to the consumers themselves, it looks like the role of gatekeepers is becoming less important than before digitization and Web 2.0.

Yet, while the market power of incumbents reduces due to digitization, there is also reason to believe that the need for certifiers goes up instead of down. Because of the increasing amount of products to choose from on the internet, the role of certifiers is growing. Additionally, Web 2.0 (e.g. Social Media) makes it possible for consumers to overflow each other with information about for example their experiences with certain products, making product information easily available. However, by doing this, they increase the amount of goods or services to choose from overall, which in turn increases the need for certifiers. In addition, Web 2.0 makes it easier for suppliers to market themselves, without intermediaries such as gatekeepers to help them. Musicians can now showcase their music on a channel like YouTube for instance, directly appealing to their target audience without going through the process of gatekeeping.

The process of digitization thus assumes that the market power of incumbents declines, together with the role of gatekeepers, but that the need for certifiers grows as the amount of products on the (digital) market increases. Digitization as a concept causes questions to rise concerning the market power of incumbents as well as the possibility of implications in the market for cultural products, as pre-purchase information is now available online. Following these questions, one might ask whether the role of gatekeepers and the market share of incumbents declines, while the role of certifiers increases due to digitization.

Due to the fact that creative goods, and therefore also music, are experience goods (Caves, 2000), the uncertainty of the value of the product is very high. With a growing amount of products to choose from, this uncertainty will increase with it, inclining the role of certifiers to grow with this uncertainty. People now more than ever need expert opinions in order to make a rational choice, being overloaded with information and products, possibly coming from not so objective sources. Consumers even get information about products on Social Media without searching for it, making the pool of musical choices even bigger.

TV-shows as certifiers

As mentioned above, the overload of information made available online increases the need for certifiers; people who tell us what we have to choose, or what is best to choose. Television shows can be of great influence, especially prime-time shows. A lot of people watch these (daily) shows which provide them with news and important facts. One can imagine that musicians playing in these shows may get more attention, as loyal viewers of the show are more likely to take what is said and stated in the show to be true. They therefore might see the musical choice of the show as an advice, and might be more likely to take an interest in that musician or band. Non-commercial shows than can have an even bigger influence, as we assume that their motivation is less likely to be corrupted by record labels.

A week-daily, live, non-commercial television show in The Netherlands which is an example of such a television show is '*De Wereld Draait Door'* (from now on abbreviated with DWDD) or directly translated into English: 'The world keeps on turning', or 'The world goes on'. Host Matthijs van Nieuwkerk is known for his fast, up-tempo talking. Every day Matthijs receives different guests, responsive to the news and topics of the day. Guests include actors, authors, politicians, musicians, newspaper or criminal reporters/journalists, etcetera. DWDD has more than half a million viewers every day, sometimes peaking to 1.8 million viewers, depending on the guests and topics (televizier.nl, 2016**).** DWDD started airing in 2005 and is still on every week-day. The show attracts people from all layers of society, due to its approachable and informative characteristics.

DWDD, amongst other things, highlights books that the makers of the show find interesting, invites authors to talk about their newly published book, or invites actors to talk about their part in a new movie. The news is also always discussed with the daily guests. Another part of DWDD is music. Every day, DWDD invites a band or musician (national as well as international artists). Matthijs van Nieuwkerk always introduces the artist(s), where he for example names the big festivals the artist(s) will play on, the big prizes they have won or have been nominated for and he names the successes of other music singles. By doing this he 'certifies' the band for the consumers, meaning that he lowers uncertainty (and search costs for the consumers). As Matthijs is a well-known figure in The Netherlands, him promoting an artist can have a big influence on the attention for this artist by consumers as well. However, Matthijs never shares his personal opinion on the band.

These artists have the opportunity to play one of their songs, but it cannot last for more than 1 minute. Some artists can even play multiple times within one show. As a lot of people watch this show every day, this 1 minute performance might determine the opinion of viewers concerning this band, thus this 1 minute can make or break them. Therefore, managers or record labels of the musicians might choose not to perform in this show, just because there is only one chance, the risk on failure is high when people do not like this one song aired.

We argue that providing airtime for unknown as well as well-known musicians and bands, in combination with the high number of viewers of the show, makes that DWDD functions as a certifier; it reduces uncertainty for the consumers, because they give an option of what is or might be a good choice of product, lowering the consumers' search costs in choosing from the big pile of music available online due to Web 2.0. This attention for musicians might lead to success for them. But then again, there are different types and 'depths' of attention, which influences the career of these musicians as explained earlier.

Musical characteristics

A person's experience with music is influenced by multiple factors other than taste, although these factors are closely linked to taste. We can differentiate between musical characteristics and aesthetical characteristics. Volume and tempo are two important musical characteristics that influence consumers' experience. Accordingly, Bruner (1990) talks about the effect music has on a person's mood. Influencing consumers' moods for the better or worse, can in turn influence their buying behaviour accordingly in a positive or negative manner. For example: *"More recently, Seidman (1981) reviewed the contributions of music to media productions (movies and education films), concluding that cognitive and affective comprehension of stimuli can be influenced. This conclusion seems to have been long held by persons in the movie industry, as is evident in the development of elaborate suggestions for marrying music to video"* (Seidman 1981, in: Bruner, 1990, p. 94).

Some conclusions made by Bruner (1990) explain that fast music is considered to be more happy and/or pleasant than slow music (Gundlach, 1935; Rigg 1940a; Scherer and Oshinsky 1977; Swanwick 1973; Watson 1942; Wedin 1972. In: Bruner, 1990), that music with high pitch is considered to be more happy or exciting than low pitched music, which is perceived as sad (Gundlach, 1935; Hevner, 1937; Rigg 1940; Watson 1942. In: Bruner, 1990) and that loud music is mostly characterized as very exciting or very happy, where soft music is often perceived as peaceful or serious (Watson, 1942. In: Bruner, 1990).

In addition, Kellaris & Rice (1993) found that music is less "irritating, sad, depressing" (p.20) at a faster tempo (in relation to music with a slower tempo), that softer music was judged as more pleasant, less sad or irritating, and more relaxing than louder music and that gender has an effect on the impact of music loudness, namely that women are more likely to be sooner irritated when music is louder, while loud music has a small positive influence on men; meaning men appraise music slightly more when it is louder. However, the authors indicate this finding to not be significant, meaning we cannot say that there is an effect of loud music on the positive appreciation by men.

Given the above, we hypothesize the following:

Consumers are more likely to give attention to fast paced music (Hypothesis 1).
and;
Consumers are more likely to give attention to high pitched music (Hypothesis 2).
And;
Consumers are more likely to give attention to loud music (Hypothesis 3).

Volume and tempo are both characteristics of music, which in great technical detail can be linked to the musical genre. Both Li, Ogihara & Lee (2003) and Creme, Burlin & Lenain, (2016) argue that technical characteristics of music, such as the frequency and amplitude, determines the genre of the song. Li et al. (2003) describe this as follows: *"The distinguishing* *characteristics are contained in the amplitude variation, and in consequence, identifying the amplitude variation would be essential for music categorization"* (p. 284). Based on this variation in amplitude, Li et al. (2003) come up with ten different music genres: Blues, Country, HipHop, Metal, Reggae, Classical, Disco, Jazz, Pop and Rock (which will be used in this research as well). Volume and tempo can differ within one genre, therefore all three variables will be taken into account.

The way music is defined, often applies to language too (and vice versa). Besson & Schön (2001) argue the following concerning language and music: *"Language is [also] composed of sequential events that unfold in time with a specific rhythm and specific segmental (phonemes) and suprasegmental (prosody) information. Moreover, the speech continuum is divided into discrete phonemes, the basic phonological unit. More generally, it is clear that both language and music are conveyed by sounds, are ubiquitous elements in all cultures, are specific to humans, and are cultural artifacts that do not correspond to natural objects"* (p. 232). We can assume that different cultures account for different music, and thus also music in different languages. This leads us to think that the language of a song, has an influence on how the listener captures the song. As DWDD is a Dutch television show, mostly Dutch citizens (with different backgrounds) watch the show. Therefore, whether a song is performed in Dutch or English, or any other (non)European language influences the perception by the consumer and ultimately their decision making process. We therefore distinguish between Dutch, English, European and Exotic languages in this research.

Visual aesthetics

Most non-cultural products today rarely break their promise and tend to do what they say. Therefore it is not surprising then that consumers increasingly make brand choices based on the aesthetic value and distinctiveness of visual design (Bloch, Brunel & Arnold, 2003). However, as we have shown before, due to the uncertain character of music, or experience goods in general, people tend to not always rely on brands to reduce their uncertainty. What we can assume is that apart from musical characteristics, people base their choices on visual characteristics or aesthetics as well. Combining both types of characteristics, consumers are even more likely to lower their uncertainty.

Within the music industry, the closest consumers can get to relying on brands is the name of the artist or even record label. As consumers then increasingly base their brand choices on aesthetic value (Bloch et al., 2003), we can say that in the case of music the fame of the artist influences the consumers' choice. These artists' well-known names then in fact function as their brand names. We may assume that an artist's fame influences the consumer's pick when they base their choice on their earlier experience. This re-picking in the end ensures a fan base to occur, based on the artist's 'brand'.

Based on the previous in combination with the literature on rational addiction as we have discussed earlier, the following is suggested:

Consumers are more likely to give attention to famous musicians (Hypothesis 4).

However, as we have seen, liking one song of an artist does not guarantee the consumer will like the next song too. This means that other factors have an influence as well on the choice making process of consumers. Visual aesthetics also have a symbolic function that influences how a product is understood and evaluated. Images of elegance, ease of use, youthfulness, durability, and innovativeness all may stem from choices marketers make in developing the appearances of new products (Forty, 1986, in: Bloch et al., 2003). Bloch et al. (2003) argue that the centrality of visual product aesthetics comprehends four dimensions: *"(1) the value a consumer assigns to product appearances in enhancing personal and even societal well-being, (2) acumen, or the ability to recognize, categorize, or evaluate product designs, (3) the level of response to visual design aspects of products, and (4) the determinancy of visual aesthetics in affecting product preferences and purchase satisfaction"* (p. 552).

In this research, several aesthetic variables were taken into account when measuring the influence of a certifier on the type of attention by the consumer. This connects to the fourth step by Bloch et al. (2003), namely the effect of visual aesthetics on product preferences. The first variable we have already: the fame of the musician(s). Secondly, we may assume that altering the visual design of the product changes the consumers' behaviour and in the end even their choices (Bloch et al., 2003). We can than say that alterations in the number of artists playing a song changes the public's opinion and actions. Therefore, the number of artists in one performance, whether it is a band or solo-artist, were documented in this research.

Given the above, we hypothesize the following:

Changes in the Group Formation of a performance causes changes in attention by consumers (Hypothesis 5).

Additionally, as herd behaviour and peer's opinions are very important in the decision making process of consumers (Caves, 2000), people experiencing the same music with the consumers play a big role. In *De Wereld Draait Door*, there is always an audience present in the studio. Consumers watching the show see this public in most cases, with the occasional close-ups of certain audience members. Following the concept of herd behaviour, we may assume that the in-show audience influences the consumers watching the show. If they have an obvious negative or positive attitude towards the playing musician(s), the consumer is likely to be influenced, leading to these opinions influencing their decision making process.

Given the above, we hypothesize:

Consumers are more likely to give attention to musicians who are positively experienced by other consumers (Hypothesis 6)

Research question

Does De Wereld Draait Door have a certifying role for artists and/or bands performing in the show? If so, what type of attention does the show generate for the musicians?
Following whether there is a DWDD-effect, it is interesting to see if there are any other variables influencing this (type of) attention. Therefore, we adopt the next follow-up question:
Are there any other (musical and/or aesthetical) characteristics influencing the type of attention for the artist or band? And if yes, which characteristics?

Methods

For this research, a quantitative content analysis is conducted. For the first part of the research, we want to know if there is a so called 'De Wereld Draait Door – effect' or not. To do this, we first look at whether there is a significant increase in attention, by comparing the amount of attention for the musician or band before they performed at DWDD and after they performed at DWDD. The different types of attention are measured in the form of the number of Google searches (1), the number of views on YouTube (2) and the number of subscribers on YouTube (3). A fourth level of attention would have been fruitful for the study, namely the number of purchases. Unfortunately, this information is not freely available (for example streams on Spotify or purchases in i-Tunes).

First of all, a Paired-Sample-T-Test analysis will be conducted in SPSS in order to see whether there is a 'De Wereld Draait Door – effect' or not. This test compares the means of our DV's before performing at DWDD and after DWDD. If there is a significant difference between them, we can talk of a 'DWDD-effect'. If we can speak of such an effect, we then conduct three regression analyses (by which we measure causality from the IV's on the DV's) to see which variables have the biggest influence on our three stages of attention, and to test our six hypotheses. These variables are explained below as our independent variables, with the three stages of attention as our dependent variables. For all analyses the programme SPSS is used.

Data

Our sample consists of 590 performances, played by 262 artists or bands (n = 262). After eliminating all cases with insufficient data (e.g. not enough information on any or all stages of attention) and after detecting all outliers by running a 'Identify outliers-test' on SPSS (see Appendix 2, Table 2) our dataset results in 536 performances played by 196 artists or bands (n = 196), which equals 74,8% of the initial data (the 5% highest and lowest values were eliminated as outliers). All these musicians and bands performed between the 22nd of March 2016 and the 23rd of March 2017 on De Wereld Draait Door. With no data between the 20th of May 2016 and the 22nd of August 2016, due to a summer break.

Our dependent variables; the number of Google searches, YouTube views and – subscribers, were measured on the day of the musician's performance on DWDD, and the day after their performance. We have chosen to do this in order to minimize the chance on other factors playing an influence on the attention of consumers (e.g. other tv-shows). Measuring the attention on the day before the performance at DWDD could lead to biased outcomes, as it is possible the musician performed at another television-show the night before he or she played in DWDD.

Our independent variables were measured through watching all (n = 196) videos from the performances on DWDD, by using the music page on the DWDD website (De Muziek Draait Door, at: dewerelddraaitdoor.vara.nl). Within the independent variables, a distinction is made between musical and aesthetical variables. The coding of these variables is done by the researcher herself, who, for the coding of musical variables, could benefit from musical expertise which came about from several years of experience in playing music. All variables were coded in one Excel file.

Dependent variables

Searches

Firstly, the number of Google Searches (hereafter called 'Searches') were collected by means of Google Trends. We look at the search hits on the name of the musician or band who performed at DWDD. The names of the songs are not used because artists sometimes sing covers, which results in misleading data in Google Trends. When using the name of the performer(s), chances are higher that the people searching watched DWDD than when we use the name of the song, as cover songs can also point to other artists performing the song (not in DWDD).

As such, we collected information on the search behaviour of people on Google in Holland. Google Trends has an option to filter per country, and even per province or state. For this research, merely data from The Netherlands is used because DWDD is only aired in Holland, thus we can only speak of an effect of DWDD on the attention of viewers within The Netherlands. If other countries were also considered, we would measure attention which could not be appointed to DWDD. Measuring merely data from the Netherlands thus increases the validity of the research.

Google Trends works with percentage points, varying from 0 to 100. A value of 100 means that on that day, the interest was the highest for that search term in a given time range. A value of 50 then means that at that point, interest was half of when it was at its peak. For this research, one month before and after the band's performance on DWDD were used to retrieve data from Google Trends. As Google Trends works with percentage points, we can only use relative data from Google Trends (as there is no absolute data available). Therefore, it is rather used to see if there is a change (positive or negative) in the attention on Google for bands or musicians who performed in DWDD, than to make statements about any exact or absolute values in relation to the attention of the consumers.

Views

For the number of YouTube views (hereafter called 'Views'), the website www.socialblade.com is used. Data like this is hard to find, as most websites like Spotify or I-Tunes tend to hide these data for the public. This information might influence market-positioning amongst other things, that is why this type of data is not published. Socialblade.com is the only (known) website to share this kind of information.

From this website, the number of views on the day of the performance and the day after the performance were retrieved. This short time span is taken in order to reduce the chance on any biases (such as when the musicians visit other television shows in the same week as DWDD, which influences the data and makes it less reliable). The chance that the musicians or bands were exposed to any other type of certifier on the same day as their performance on DWDD, is considerably smaller than when we would take a time span of, let us say, a week.

Subscribers

The number of subscribers is retrieved from the same website and in the same manner as the number of views (www.socialblade.com).

Concerning both Views and Subscribers, the YouTube channel posting most videos of the musician(s) was used, when possible. In a lot of cases this is the (official) channel of the band itself. In other cases, the Record Label posts all videos. When there was more than one channel to choose from, the channel with the highest number of followers and/or views was chosen. For the sake of preciseness, for all data the artists' or bands' names were used, instead of the names of songs they performed.

DWDD-Index

In order to do regression analyses with the dependent variables (DV), an index was constructed for each DV (see Appendix 2, Image 1). This index is based on the relative difference between the number of searches/views/subscribers before and after DWDD. This number was standardised (by adding the lowest value to all other values). These standardised values (the z-score) resulted in our DWDD-indexes.

Independent variables

After we will see whether we can talk about a ‘DWDD-effect’, the next step is to see if other variables can influence the attention DWDD generates. Here we make a distinction between musical characteristics and visual aesthetics. In line with Bruner (1990) and Kellaris & Rice (1993) we decided to code the following musical characteristics: The Language of the song (1), Genre (2), Volume (3), Tempo (4) and Pitch (5) . Most of the variables were coded on a 5-point Likert scale, ranging from for example very slow to very fast (in the case of Tempo). For an extended overview of the scales, see Appendix 1, Table 1. The variables coded according to a 5 point Likert scale can be put directly into our model. For other (categorical) variables (such as genre for example), a dummy variable was constructed in order to be able to use the variables in a regression model (see Appendix 1 , Table 1). As mentioned above, this coding is done by the researcher herself, who could benefit from musical expertise which came about from several years of experience in playing music. This experience accounts for the ability to read notes and to clearly distinguish between different volumes, tempos and pitches.

For the visual aesthetics, the following variables are developed: The Group Formation of the musicians/band (1), the Fame of the Artist(s) (2) and the Reaction of the Public (3). The fame of an artist is measured on whether this artists finds him- or herself in the Top 100 of 2016 (yes or no), made by the MediaMarkt Top40, the most well-known music chart in The Netherlands and the reaction of the public is also measured with a 5 point Likert-scale, ranging from very negative to very positive (compared to the reaction of the public for other performances in DWDD on other days).

As Matthijs van Nieuwkerk names the successes of the artist(s) in the show, he never shares his personal opinion. Therefore, his introduction will not be taken into account in this research, as we cannot code it as positive or negative, because he shares the same information for all artists.

Control variables

We expect other, more basic variables, to have an influence on attention by consumers as well. What this effect is and why cannot be said upfront, therefor we include some control variables in this research: Amount of songs played within 1 show of DWDD (1), Gender of the artist(s) (2), Age of the artist(s) (3), Nationality of the artist(s) (4), Skin colour of the artist(s) (5) and whether the song is a cover or not (6). In total, this brings us to a number of 14 variables.

Additionally, to complete the overview, the next data was gathered as well: coded performances (ranging from M1a,b,c.. to M262a,b,c..), the name of the artist or band, the name of the song performed and the date of the performance. As some artists performed more than once on the same DWDD show, all different songs are documented. However, after coding a few performances, it became visible that only variables like pitch, volume and tempo differed, while others remained the same. Therefore, only the famous ‘DWDD-minute’ was coded. This is based on the fact that all artists and bands were (only) able to play one minute of a song, which equalized the chance for all bands to be picked up by the audience, thus a constant factor in our analyses.

Results

<u>'DWDD-effect'</u>

First of all, we wanted to see if *De Wereld Draait Door* really has a significant effect on the attention of consumers. In order to see if there is, a Paired Sample-T-Test was conducted in SPSS. This test allows us to see if the two measures (before and after) for each type of attention significantly differs from one another. If yes, we can say that there is a DWDD-effect for each type of attention. Below in Table 1 we can see the outcome of this test.

Paired Samples Test

		Paired Differences							
					95% Confidence Interval of the Difference				
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper	t	df	Sig. (2-tailed)
Pair 1	Google Searches Before DWDD - Google Searches After DWDD	-62,484	36,285	2,632	-67,677	-57,292	-23,737	189	,000
Pair 2	Views Before DWDD - Views After DWDD	-85222,398	251146,98	17939,070	-120601,91	-49842,891	-4,751	195	,000
Pair 3	Subscribers Before DWDD - Subscribers After DWDD	-75,2908	185,1316	13,2237	-101,3706	-49,2110	-5,694	195	,000

Table 1. Paired Sample-T-Test for all three types of attention [Searches, Views & Subscribers]

This table shows that there are three "pairs" of observations on which this test is conducted. Pair one is for the number of Google Searches, pair two for the number of views and pair three for the number of subscribers, each time, the number of Searches/Views/Subscribers before and after the performance on DWDD was inserted. For the first pair, the Google Searches, the hypothesis is as follows:

H0 = There is no difference in the average number of Google Searches before a DWDD performance and after a DWDD performance.
and;

H1 = There is a difference in the average number of Google Searches before a DWDD performance and after a DWDD performance.

For the number of YouTube views, our hypothesis is as follows:

H0 = There is no difference in the average number of YouTube views before a DWDD performance and after a DWDD performance.
and;
H1 = There is a difference in the average number of YouTube views before a DWDD performance and after a DWDD performance.

And lastly, the hypothesis for the number of YouTube subscribers:

H0 = There is no difference in the average number of YouTube subscribers before a DWDD performance and after a DWDD performance.
and;
H1 = There is a difference in the average number of YouTube subscribers before a DWDD performance and after a DWDD performance.

With $\alpha = 0.05$, it means that the significance level should be 0.05 or lower, to be able to reject H0 and accept H1 with 95% certainty. If the significance level is higher than 0.05, we cannot reject H0. The Paired-Level-T-Test shows a 0.00 significance for all pairs (all types of attention). This means that we can reject all H0's, and accept the H1's. This means that there certainly is a DWDD-effect, and that it applies for all types of attention. Thus, we can say that *De Wereld Draait Door* has a significant effect on the amount of attention consumers have for musicians who performed in the television-show.

Before we explained why we set-up the indexes. Adding to these reasons is the very strong significance of the Paired Sample-T-Test for the three types of attention. With the index we assume to get better insights in other analyses.

Correlations between DV's

As we cannot unconditionally assume that all our dependent variables are or are not connected to each other, we have chosen to do a correlation test. This technique allows us to see if there are any relations between our DV's (see Table 2 below). For this analysis we used our indexes (z-scores).

Table 2.

Correlation test for all types of attention (z-score) [Searches, Views & Subscribers]

Correlations

		z-score Searches	z-score Views	z-score Subcribers
z-score Searches	Pearson Correlation	1	,106	,163*
	Sig. (2-tailed)		,139	,023
	N	196	196	196
z-score Views	Pearson Correlation	,106	1	,373**
	Sig. (2-tailed)	,139		,000
	N	196	196	196
z-score Subcribers	Pearson Correlation	,163*	,373**	1
	Sig. (2-tailed)	,023	,000	
	N	196	196	196

*. Correlation is significant at the 0.05 level (2-tailed).

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

Table 2 shows that:

- The number of Searches is positively and weakly correlated to the number of Subscribers (with $\alpha = 0.05$)
- The number of Views is positively and strong(er) correlated to the number of Subscribers (with $\alpha = 0.01$)
- And thus, the number of Subscribers is correlated to the number of Searches as well as the number of Views

Thus, we can say that the chance is high that the people (consumers) who subscribed themselves on the YouTube channel of an artist or band they have seen on DWDD, are the same people who have searched for this same artist or band on Google.

Secondly, we can say that the chance is high that the people (consumers) who subscribed themselves on the YouTube channel of an artist or band they have seen on DWDD, are the same people who have viewed (a) video(s) on the YouTube channel of that artist or band.

However, there is no correlation between the number of searches and the number of views. This means that the chance is high that the viewers are other people than the searchers. While the other two combinations did correlate, it leads us to think that the chance is low that consumers go through all stages of attention. Different people follow different stages (with, in most cases, a maximum of two stages). It assumes (but without any certainty) that people either search for the artist on Google *or* that they view the video on YouTube, before they subscribe themselves (if they do) on the YouTube channel by that artist. It is a probability that people do not need both stages (searching and viewing) to arrive at the deepest stage in this research; subscribing.

Multivariate analysis of variance

As we have seen, our DV's correlate to each other. However, it is not in such a strong manner that one DV is a necessary condition for the other DV('s). For this reason, we have chosen to do a multivariate analysis (MANOVA), so that we keep the possibility open and included that our DV's are related. We chose this test over tests where one DV is a necessary condition for the next one, like in a two-stage model like the Heckman two-stage, where the probability of one relationship is being calculated, which in turn goes into the next calculation of a relation.

The results of this MANOVA test tells us that the (control) variables Nationality, Fame and Skin Colour significantly variate (with $\alpha = 0.05$) in at least one of our DV's (see Appendix 2, Table 3.1). In table 3.2 (Appendix 2) we can see that Nationality significantly variates in the DV of Subscribers, Fame variates in the DV of Searches and Skin Colour variates in the DV of Subscribers (all with $\alpha = 0.05$). The next step is to do a regression analysis for all separate DV's, in order to see which IV's influence the separate DV's. We will do these tests separate as we have seen before that not all DV's correlate. We will have to see whether the separate regressions are significant models, in order to say something about the results of these tests. If a model is not significant, we cannot draw any conclusions on the causality between the IV(‘s) and DV.

Significance of the Regression models

In order to say something about the influence of our IV’s on the DV’s, the overall model of the regression has to be significant. Below we explore this per DV.

Searches

Table 3.

Model Summary for regression analysis Searches.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,491[a]	,241	,182	33,6139

a. Predictors: (Constant), Cover, NewReactionPublic, NewPitch, Volume, NewSkinColour, NewFame, NewGroupFormation, Age, Number of Performances in 1 show by 1 artist, Gender, NewGenre, Tempo, NewLanguage, NewNationality

b. Dependent Variable: z-score Searches

Table 4.

ANOVA test for significance of the model for DV Searches.

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	64474,968	14	4605,355	4,076	,000[b]
	Residual	203381,319	180	1129,896		
	Total	267856,287	194			

a. Dependent Variable: z-score Searches

b. Predictors: (Constant), Cover, NewReactionPublic, NewPitch, Volume, NewSkinColour, NewFame, NewGroupFormation, Age, Number of Performances in 1 show by 1 artist, Gender, NewGenre, Tempo, NewLanguage, NewNationality

Table 3 shows us that our model correlates with 0.491 (R) with our DV Searches and that it explains 24.1% (R^2) of this DV. Table 4 tells us that this model is significant by 0.000. This means we can use this model to say something about the outcomes.

Views

Table 5.

Model Summary for regression analysis Views.

Model Summary[b]				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,232[a]	,054	-,020	10,750815

a. Predictors: (Constant), Cover, NewReactionPublic, NewPitch, Volume, NewSkinColour, NewFame, NewGroupFormation, Age, Number of Performances in 1 show by 1 artist, Gender, NewGenre, Tempo, NewLanguage, NewNationality

b. Dependent Variable: z-score Views

Table 6.

ANOVA test for significance of the model for DV Views.

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1180,143	14	84,296	,729	,743[b]
	Residual	20804,403	180	115,580		
	Total	21984,546	194			

a. Dependent Variable: z-score Views

b. Predictors: (Constant), Cover, NewReactionPublic, NewPitch, Volume, NewSkinColour, NewFame, NewGroupFormation, Age, Number of Performances in 1 show by 1 artist, Gender, NewGenre, Tempo, NewLanguage, NewNationality

Table 5 shows us that our model correlates with 0.232 with our DV Views and that it explains 5.4% of this DV. However, table 6 tells us that our model is not significant. This means we cannot make any statements about the influence of our IV's on our DV Views.

Subscribers

Table 7.

Model Summary for regression analysis Subscribers

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,389[a]	,152	,086	,986619

a. Predictors: (Constant), Cover, NewReactionPublic, NewPitch, Volume, NewSkinColour, NewFame, NewGroupFormation, Age, Number of Performances in 1 show by 1 artist, Gender, NewGenre, Tempo, NewLanguage, NewNationality

b. Dependent Variable: z-score Subcribers

Table 8.

ANOVA test for significance of the model for DV Subscribers

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	31,327	14	2,238	2,299	,006[b]
	Residual	175,215	180	,973		
	Total	206,542	194			

a. Dependent Variable: z-score Subcribers

b. Predictors: (Constant), Cover, NewReactionPublic, NewPitch, Volume, NewSkinColour, NewFame, NewGroupFormation, Age, Number of Performances in 1 show by 1 artist, Gender, NewGenre, Tempo, NewLanguage, NewNationality

Table 7 shows us that our model correlates with 0.389 (R) with our DV Subscribers and that it explains 15.2% (R^2) of this DV. Table 8 tells us that this model is significant by 0.006. This means we can use this model to say something about the outcomes.

Our regression analyses for the DV's Searches and Subscribers are significant (respectively by 0.000 and 0.006 with $\alpha = 0{,}050$). We can use both models to interpret the results. However, we cannot do the same for our dependent variable Views, as our regression model for Views is not significant. We therefor take a closer look into the insignificance of this model.

Insignificance of Regression Views – Outliers & Homoscedasticity

As we have stated before, our data concerning the Views (the index) was checked on outliers by running a 'Test-Outliers' test in SPSS (see Appendix 2, Table 2). The reason for running this test was caused by the insignificance of the regression model of our DV Views (see Appendix 2, Table 4 for the regression outcome before eliminating the outliers). However, after eliminating these outliers, the model remained insignificant.

In order to get a better understanding of why our model is insignificant, we ran a test for homoscedasticity (a condition which has to be met in order to make statements based on the regression model [see Appendix 2, Graph 1]). This test shows that our data is skewed, meaning that the condition for homoscedasticity is not met (based on deviations in the plot). This means that the variances differ significantly, meaning we talk of heteroscedasticity. Heteroscedasticity has a big influence on the standard error and in turn on the confidence intervals and the significance of the parameter. Therefore, we will not make any statements based on the regression model for the DV Views. Our other two models (for Searches and Subscribers) do meet the condition for homoscedasticity.

A possible reason for the different variances could be that one person can be accounted for multiple views (while this is not the case for the DV Subscribers; 1 subscription stands for 1 person). Therefore, the number of views often run into millions, while extra views a day often are a few hundred or thousand. The relative increase or decrease is thus very low (while the increase in views after DWDD compared to the average daily increase might be significant when we look at the difference in means: 5827 before DWDD and 85222 after DWDD; see Appendix 2, Table 5). We can say that when the start amount of views is very high (millions), the relative increase is very low. On the other hand, when the start amount of views is low, the relative increase is much higher. This assumes to account for the different variances in our model. However, for further analyses, the regression model of DV Views will not be taken into account.

Regression & accepting/rejecting our hypotheses

As we have seen, the regression models for our DV's Searches and Subscribers are significant (see table 4 & 8 above). As we cannot use one regression model (with all our DV's) to accept or reject our hypotheses, we will make a distinction between the two DV's in doing this (and thus do separate regressions).

Searches

We will first accept or reject our six hypothesis (of musical and aesthetical characteristics) based on the regression analysis of the DV Searches (see Appendix 2, Table 6). Other findings will be explained later on. For all regression tests we use $\alpha = 0.05$.

Hypothesis 1: *Consumers are more likely to give attention to fast paced music.*

(H0 = Consumers are not more likely to give attention to fast paced music).

The IV Tempo in our model does not significantly influence the DV Searches (sig.= 0.231). Therefore, we cannot reject H0 and say that consumers are more likely to give attention, in the form of Google Searches, to fast paced music. Even if the test were to be significant, in our model, Tempo correlates (insignificantly) negatively with Searches, meaning that it would be more likely for slower paced music to have a positive influence on the number of Google Searches. However, we cannot state this.

Hypothesis 2: *Consumers are more likely to give attention to high pitched music.*

(H0 = Consumers are not more likely to give attention to high pitched music).

The IV Pitch also does not significantly influence the number of Google Searches (sig.= 0.088). Therefore, we cannot reject H0 and say that high pitched music has a positive influence on the number of Google Searches.

Hypothesis 3: *Consumers are more likely to give attention to loud music.*

(H0 = Consumers are not more likely to give attention to loud music).

The IV Volume does not significantly influence the number of Google Searches (sig.= 0.500). Therefore, we cannot reject H0 and say that loud music positively influences the number of Google Searches. Even if the relation was significant, Volume would have a negative correlation (because of the direction) with DV Searches, meaning that consumers would be more likely to give attention to softer music. However, we cannot state this with any certainty.

Hypothesis 4: *Consumers are more likely to give attention to famous musicians.*

(H0 = Consumers are not more likely to give attention to famous musicians).

The IV Fame does significantly influence the number of Google searches (sig.= 0.002). Therefor we can reject H0 and accept H1. However, our dummy model (Appendix 1, Table 1) indicates that 0 = is famous, 1 = not famous. This means that (because our influence is in a positive direction) we have to treat our H4 as if the influence on it has a negative direction. This means that when an artist is already famous, he or she gets less attention in terms of Google Searches. This finding is not in line with the literature (Bloch et al., 2003), as it suggest that in the case of product uncertainty, consumers base their choice on positively experienced brands. The finding supports our assumption that within the music industry, it is harder to talk about branding, which leads to that there is no security of warranties or reducing uncertainty by branding. Therefore, the statements made concerning branding are less likely to apply in the music industry.

Hypothesis 5: *Changes in the Group Formation of a performance causes changes in attention by consumers.*

(H0 Changes in the Group Formation of a performance does not cause changes in attention by consumers).

Our IV Group Formation does not significantly influence the number of Google Searches (sig.= 0.291). Thus, we cannot reject H0 and say that changes in the Group Formation of a performance on DWDD causes changes in the number of Google Searches.

Hypothesis 6: *Consumers are more likely to give attention to musicians who are positively experienced by other consumers.*

(H0= Consumers are not more likely to give attention to musicians who are positively experienced by other consumers).

The IV Reaction of the Public does not significantly influence the number of Google Searches (sig.= 0.090). Therefore, we cannot reject H0 and say that the reaction of the public in the studio of DWDD influences the number of Google Searches.

Subscribers

We will now accept or reject the same six hypothesis based on the regression analysis of the DV Subscribers (see Appendix 2, Table 7). Other findings will be explained later on. For all tests we use $\alpha = 0.05$.

Hypothesis 1: *Consumers are more likely to give attention to fast paced music.*

(H0 = Consumers are not more likely to give attention to fast paced music).

The IV Tempo does not significantly influence the number of Subscribers (sig.= 0.863). Therefore, we cannot reject H0 and say that fast paced music positively influences the number of Subscribers on YouTube.

Hypothesis 2: *Consumers are more likely to give attention to high pitched music.*

(H0 = Consumers are not more likely to give attention to high pitched music).

The IV Pitch does significantly influence the number of Subscribers (sig.= 0.050). Therefore, we can reject H0 and accept H1. We can state that higher pitched music positively influences the number of Subscribers on YouTube. This supports literature stating that high pitched music positively influences consumer liking, as consumer liking is in our research described as attention (Bruner, 1990; Kellaris & Rice, 1990). However, we do not state that high pitch influences consumer liking, but we do state that high pitched music has a positive influence on the attention given by consumers. This might be linked back to consumer liking, but is not what is stated here.

Hypothesis 3: *Consumers are more likely to give attention to loud music.*

(H0 = Consumers are not more likely to give attention to loud music).

The IV Volume does not significantly influence the number of Subscribers (sig.= 0.378). Therefore, we cannot reject H0 and say that loud music positively influences the number of Subscribers on YouTube. Even if the relation was significant, Volume would have a negative correlation with DV Subscribers (just as was the case with Google Searches), meaning that consumers would be more likely to give attention to softer music. However, we cannot state this.

Hypothesis 4: *Consumers are more likely to give attention to famous musicians.*

(H0 = Consumers are not more likely to give attention to famous musicians).

Our IV Fame does not significantly influence the number of Subscribers (sig.= 0.342). Therefore we cannot reject H0 and say that whether an artist is famous or not influences the number of Subscribers on YouTube.

Hypothesis 5: *Changes in the Group Formation of a performance causes changes in attention by consumers.*

(H0 Changes in the Group Formation of a performance does not cause changes in attention by consumers).

The IV Group Formation does not significantly influence the number of Subscribers (sig.= 0.667). However, when this relation would have been significant, Group Formation is negatively correlated to the number of Subscribers. As 0 = solo artists and 1 = More than 1 person in the dummy variable, it would be the case that solo artists have a more positive influence on the number of Subscribers than groups of more than 1 artists would have. This then also directly means that Group Formation does cause changes in the number of Subscribers on YouTube. However, we cannot state this with any certainty.

Hypothesis 6: *Consumers are more likely to give attention to musicians who are positively experienced by other consumers.*

(H0= Consumers are not more likely to give attention to musicians who are positively experienced by other consumers).

Our IV Reaction of the Public does not significantly influence the number of Subscribers (sig.= 0.401). Therefore, we cannot reject H0 and say that a positive reaction of the public in the studio of DWDD has a positive influence on the number of Subscribers on YouTube.

Concerning our hypotheses, we can accept one per DV. For Searches this is the Fame of an artist, and for Subscribers it is the Pitch of a song. We will now look at if there are any other (of our control) variables significantly influencing these DV's.

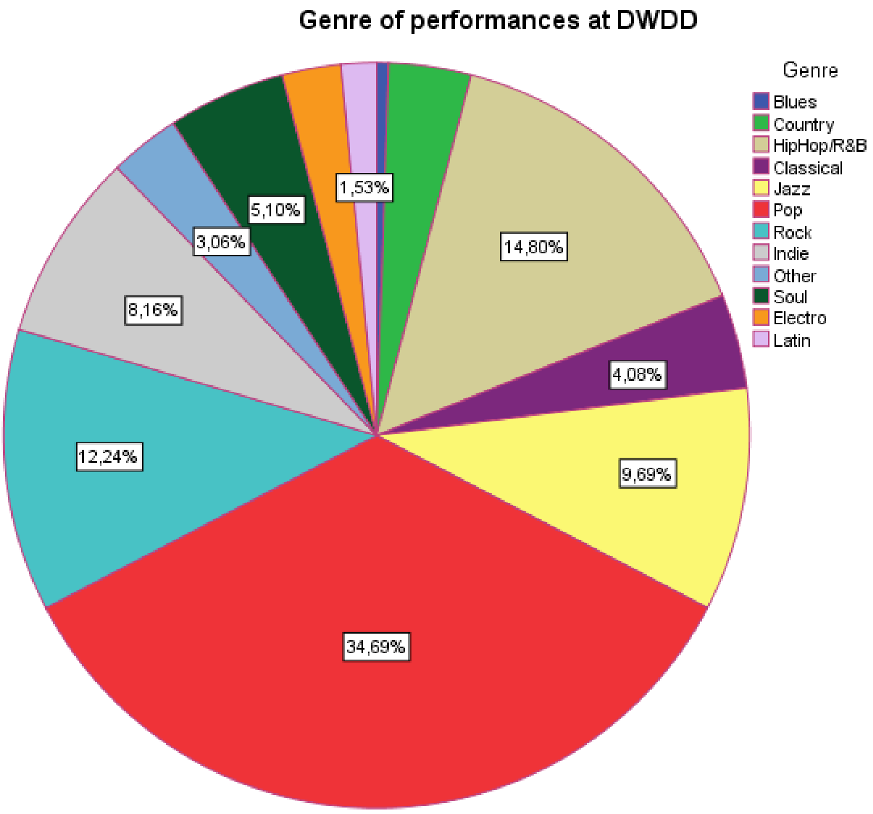
Other significant findings

Before we explore if there are any other significant findings influencing our DV's, we will describe some findings concerning the control variables.

First of all, in Graph 1 below we can see that DWDD mostly showcases pop-music. Additionally, Pop, Jazz and Rock make up for more than half of all (n = 196) performances. Worth mentioning is that the Indie genre makes up for 8.16% of all performances, which is a lot concerning the unconventional attribute of the Indie genre.

Graph 1.

Pie chart of Genre in percentages



Secondly, 60.7% of all artists or bands performing in DWDD are all male bands or solo acts (see Appendix 2, Table 8). Also, 48.0% of the performers are 18 to 30 years old, 58.7% of all performances are sang in English (87.2% in English or Dutch), 63.8% of all performers have a Dutch Nationality, 52.6% are either performing in a classic band or solo but with back up musicians and that 66.3% of all performers in DWDD have a white skin colour (see Appendix 2, Tables 9 to 13)

We will now proceed with other significant findings concerning the regression analyses of our DV's Searches and Subscribers.

Searches

The IV Number of Performances in 1 show significantly influences (with a positive direction) the number of Google Searches (sig.= 0.018). This means that more performances by an artist within one show of DWDD (with a maximum of 5 performances in one show, and a mean and median of 2 performances per show) positively influences the number of Google Searches, compared to less performances in one show.

Secondly, our IV Language of the Song also significantly and positively influences the number of Searches (sig.= 0.048). We can say that, because our dummy variable consists of 0 = Dutch and 1 = non-Dutch, songs performed in another language than Dutch positively influences the number of Google Searches, compared to songs performed in the Dutch language.

Subscribers

Our IV Nationality significantly influences (with a negative direction) the number of Subscribers. As our dummy variable consist of 0 = European (also Dutch) and 1 = non-European, we can say that when artists have European nationality, the number of Subscribers is positively influenced, compared to non-European nationalities.

Additionally, the IV Skin Colour also significantly influences (with a positive direction) the number of Subscribers on YouTube (sig.= 0.023). As our dummy variable consists of 0 = white and 1 = not white, we can say that artists with black or mixed skin colour, as well as bands with mixed skin colours in them, have a positive influence on the number of subscribers, compared to white artists.

Thirdly, IV Cover significantly influences (with a positive direction) the number of Subscribers (sig.= 0.045). This means that (because 0 = yes it is a cover, and 1 = no it is an original song) original songs instead of covers positively influence the number of Subscribers on YouTube.

The correlation model discussed below supports all significant regression findings (see Appendix 2, Table 14).

<u>Correlations between IV's</u>

When we look at the correlation table (between all IV's and DV's), we see that correlations between our DV's as discussed before. We will focus on correlations between our IV's and between IV's and DV's in the following section.

First of all, we see that there are multiple correlations apparent in our model. Some findings are somewhat less striking than others; it is for example not strange that Volume and Tempo positively correlate with Genre, because as discussed, genres can be divided based on their frequencies and amplitudes, which can be related back to characteristics such as tempo and volume. Therefore, these correlations support the literature (Li et al, 2003; Creme et al, 2016). Another such logical finding is that pitch quite strongly and negatively correlates to gender, which in our case means that the more men there are in a group (or solo), the lower the pitch of the song. Additionally, Skin Colour strongly and positively correlates with Nationality, which means that darker and mixed skin colours are linked to non-European nationalities. These findings seem logical, but can be seen as a support for the reliability of our model and research and, as stated above, the findings support the theory.

Our correlation model shows that the Number of Performances is positively correlated to pitch, meaning that the more performances an artist does on the show, the higher the pitch. This findings too supports the theory on pitch and that high pitched music influences consumer liking, or in our case attention by the consumer (Gundlach, 1935; Hevner, 1937; Rigg 1940; Watson 1942. In: Bruner, 1990). Interestingly, the Number of Performances is also positively correlated with Cover, meaning that the more performances an artists does in DWDD, the more authentic songs (non-covers) are performed, and in comparison, artists who perform 1 song in the show are more likely to do a cover. This is interesting, as Cover is positively correlated to the number of Subscribers as we have seen above. Thus we can assume that the more songs an artist performs in a show, the more Subscribers (though this is not significantly the case in our model, but is assumed indirectly). Adding to this is that Group Formation is also positively correlated to Cover, meaning that groups of artists or bands are more likely to sing original songs.

Additionally, we can see that Age is negatively correlated to Language, as well as Fame, Tempo and Cover. This leads to the assumption that the older the performers are on DWDD, the more famous they are, the slower their songs are and the more likely it is that they do not sing an original song, but a cover. The negative correlation between cover and age, and the positive correlations between cover and number of searches and subscribers (more attention for original songs), leads us to think that the high percentage (48%) of artists with ages between 18 and 30 is due to the fact that consumers give more attention to original songs instead of covers, and thus automatically give more attention to younger artists.

Moreover, Language is strongly and positively correlated to Fame, meaning that performers singing in another language than Dutch have more fame than performers singing in Dutch, even though their nationality is Dutch (as Fame is negatively, but insignificantly correlated to Nationality). What is more, is that Nationality is positively correlated to Genre, Tempo and Skin colour and negatively correlated to Group Formation. Meaning that we assume that non-European artists are more likely to have a black or mixed skin colour (as discussed above), that they sing in a faster Tempo, more often in genres other than Pop music and that they more often perform solo or solo but backed up by a band.

Adding to this is that Group Formation is also positively correlated to Cover, meaning that groups of artists or bands are more likely to sing original songs. Also, Tempo is correlated to Cover, meaning that the faster paced songs are more likely to be original songs, and that the slower paced songs are likely to be the songs which are covered. As Volume is also strongly and positively correlated to Tempo, it leads us to believe that more attention is given to up-tempo, original and louder music, which in turn leads our findings to support the literature on the influence of both Volume and Tempo on consumer liking (and in our case attention), without these IV's directly having a positive influence on the number of Searches or Subscribers.

Our regression analysis on the dependent variables Number of Google Searches and Number of Subscribers on YouTube and our correlation analysis between our independent variables leads us to set up a profile for musicians for whom it is most likely that DWDD creates attention (this is a presumption based on our findings). Our results of the regression analyses in combination with the correlations between the IV's leads us to set up the profile as follows; artists are: Between 18 – 30, all have a white skin colour, are a classic band which is not famous in Holland yet, play Pop music, have a Dutch Nationality but sing in English, perform original songs which are high pitched, fast paced and loud and perform more than 1 song in the show (also see Table 9 below).

Table 9.

Profile for musicians for whom DWDD presumably generates the biggest increase in attention.

Variable	**Most beneficial value**
Age	18 – 30
Skin Colour	All white
Group Formation	Classic band
Fame	No
Genre	Pop
Nationality	Dutch
Language of the performed song	Non-Dutch (English)
Cover	No
Pitch	High
Tempo	Fast
Volume	Loud
Number of Performances	More than 1

Conclusion

First of all, our research proved that *De Wereld Draait Door* has a strong significant influence on the attention of consumers, considering the number of Google Searches and the number of Subscribers on YouTube. We can say that there is a 'De Wereld Draait Door – effect'. By this, we have shown that certifiers have an important role in informing consumers nowadays, as we live in an era of 'prosumation' and where consumers are overloaded with information, leading to an increase in uncertainty, especially for industries like the music industry, where goods are considered experience goods. The impact of certifiers clearly comes to the fore. This growing importance of certifiers is relatively new and has not been researches in any published papers yet.

Our research also assumes that consumers are more likely to either search an artist on Google or view their song(s) on YouTube, before they commit to a deeper level of attention: subscribing on the artist's YouTube channel. Our results indicate that at first glance, in order to spark enthusiasm and attention for the artist, visual aesthetics are most important. When it comes to the deepest form of attention, musical variables are most important. This might indicate that in the end, consumer bonding depends on the musical variables, while aesthetic variables are important only at first glance, but in turn influences the deepest form of attention (bonding).

Our research has lead us to set up a profile. As DWDD is an example of a certifier within the music industry, this profile is likely to apply to other prime time daily (non-commercial) television shows (certifiers) as well. The other way around, artists can also use this in considering whether or not to perform on DWDD, lowering their risk of failure. It is interesting to know whether TV-shows like DWDD are aware of this information, leading them to use it to create more attention for their show as well and for the bands performing on the show.

Discussion & Recommendations for further research

As we have seen, our musician profile (Table 9) is applicable to DWDD, and with that possibly other TV-shows as well. However, this TV-show has to have the same viewer profile as DWDD, thus future studies could address the viewer profile of DWDD, as it can then be researched if our 'musician profile for increasing attention' is applicable to other television shows with the same viewer profile as well.

Additionally, it is worthwhile to investigate whether shows like DWDD are aware of the information (the musician profile) which creates most attention. If not, this information could be of great importance for marketing.

As our research proves that television-show DWDD plays a big role as a certifier, it could have a big influence on the democratisation of the music industry. As the barriers for watching a television show, especially one on a public channel, are rather low, shows like DWDD have a large outreach. Shows like this have the power to break through the power of the traditional players in the music industry, such as record labels, especially because we have seen that attention is higher for artists who are not yet famous.

As our musician profile (Table 9) for whom DWDD generates the biggest increase in attention can have a positive influence, it also shows that music who gets the most attention (through DWDD) is rather standard and conventional music. This can have a negative influence concerning opportunities for more unconventional music. Though the stage of DWDD is provided for very different types of music, including Indie for example, the substantial bigger part of the airing time goes to popular music. Creating a not so big of an opportunity for consumers to expand their music knowledge. Themes like this one as well as ethnic ones rising out of this research can be of great help in areas such as Cultural Economics and Cultural Sociology.

Limitations

Of course, as any study, ours has limitations as well. Even though we collected and constructed many of the variables ourselves, our statistical model is not perfect. We had to make some pragmatic choices, such as the time span between the data we collected. As we have said, data was collected on the day of the performance and the day after the performance, for the sake of reducing the chance on biased data. However, if some consumers have for example viewed a YouTube video on the same night as the performance of DWDD, it could have influenced our data.

Another example is that the name of the band or artist could have an influence on our data concerning Google Searches, when this name is a commonly used word in either Dutch or English (e.g. '*Spoon*'). People who wanted to look up information on spoon as an object, influence the number of Google Searches. This was not often the case, as we only researched Google Searches in the Netherlands, and bands in most cases had English names.

Thirdly, concerning YouTube, the information by Record Label channels was used when the artist him/-herself did not have their own channel. The number of views is influences as this Record Label also distributes music by other artists. Though the small time span made that the chance of other music videos influencing the amount of Views is as small as possible. Adding that we did not conclude anything based on the model for Views, as this model was statistically not significant.

Lastly, the data gathering was done by one researcher. Other researchers might code the independent variables (such as the musical ones) in another manner.

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Appendix 1
Codebook

The dataset of this research is available upon request.

Table 1.

Variable explanation and coding possibilities.

Variable	Explanation	Coding options	Dummy variable
Gender	Gender of all (band) members	0 = All female, 1 = Bigger part female, 2 = Equally mixed, 3 = Bigger part male, 4 = All Male	No
Age	Age of all (band) members	0 = Below 18, 1 = 18 - 30, 2 = 31 - 50, 3 = Over 50	No
Language of Performance	The language performers sing in	0 = Dutch, 1 = English, 2 = Other European, 3 = Exotic (non-European), 4 = other, 5 = no singing, 6 = mixed	Yes (Dutch/non-Dutch) [NewLanguage]
Nationality	Nationality of the (band) members (if mixed; the dominant nationality was chosen)	0 = Dutch, 1 = European (non-Dutch), 2 = American, 3 = Exotic, 4 = other	Yes (European/ Non-European) [NewNationality]
Genre	Genre of the song performed in DWDD	0 = Blues, 1 = Country, 2 = HipHop/R&B, 3 = Metal, 4 = Reggae, 5 = Classical, 6 = Disco, 7 = Jazz, 8 = Pop, 9 = Rock, 10 = Indie, 11 = Other,	Yes (Pop/Non-pop) [NewGenre]

		12 = Soul, 13 = Electro, 14 = Latin	
Group Formation	Formation of the band at time of performance in DWDD	0 = solo artist, 1= solo but backed up with musicians 2 = classic band (singer, 2 guitars, drums), 3 = band + copper instrument(s), 4 = orchestra, 5 = other, 6 = Duo or trio (with or without band), 7 = Choir	Yes (solo/non-solo) [NewGroupFormation]
Fame	The fame of the performers in DWDD (according to 'Top40' top 100 of 2016	0 = Yes, 1 = No, 2 = classic (national) band	Yes (famous/not-famous) [NewFame]
Volume	The volume of the song performed in DWDD	0 = Very soft, 1 = soft, 2 = not soft / not loud, 3 = loud, 4 = very loud	No
Tempo	The tempo of the song performed in DWDD	0 = Very slow, 1 = slow, 2 = not slow / not fast, 3 = fast, 4 = very fast	No
Reaction Public	The reaction of the public present in the studio of DWDD at the time of the performance (if recorded on tape)	0 = very bad reaction, 1 = bad reaction, 2 = neutral reaction, 3 = positive reaction, 4 = very positive reaction, 5 = different reactions, 6 = no reaction on film	Yes (no or bad/neutral/positive) [NewReactionPublic]
Pitch	The pitch of the song performed in DWDD	0 = Very low, 1 = low, 2 = medium, 3 = high, 4 = very high, 5 = no singing	Yes (5=0) [NewPitch]

Skin Colour	The skin colour of the performer(s) in DWDD (with mixed in band used when there are musicians with different skin colours within one band)	0 = White, 1 = Black, 2 = Mixed race, 3 = Mixed in band, 4 = Other	Yes (white/non-white) [NewSkinColour]
Cover	Whether the song a band/musician performs is a cover (someone else's song) or not	0 = Yes, 1 = No	No

Appendix 2

Tables & Graphs

Table 2.

Exploring outliers for number of Views.

Descriptives

			Statistic	Std. Error
Number of extra views	Mean		124118,301	33060,6902
	95% Confidence Interval for Mean	Lower Bound	58935,728	
		Upper Bound	189300,873	
	5% Trimmed Mean		54791,203	
	Median		2070,000	
	Variance		2251599027 59,206	
	Std. Deviation		474510,171 4	
	Minimum		-2500000,0	
	Maximum		2730000,0	
	Range		5230000,0	
	Interquartile Range		31078,5	
	Skewness		2,471	,169
	Kurtosis		17,450	,337

Extreme Values

			Case Number	V1	Value
Number of extra views	Highest	1	12	M16	2730000,0
		2	52	M70a	2600000,0
		3	77	M100a	2580000,0
		4	95	M122a	2210000,0
		5	74	M97a	1830000,0
	Lowest	1	42	M53a	-2500000,0
		2	43		-501480,0
		3	154	M188a	-64130,0
		4	193	M244a	-16440,0
		5	41	M52a	-3170,0

Image 1

Example of the indexes used in Excel.

	A	B	C	O	P	Q	R	S	T	U	V	W	X
1		**Name artist**	**Name song**	**Absolute Δ**	**z-score (st**	**Absolute Δ**	**Relative Δ**	***100 View**	**z-score (st**	**Absolute**	**Relative Δ**	***100 Subs**	**z-score (st**
2	**M1a**	Rachèl Louise	Big Girls	95	160	-230	-0,002	-0,217	6,445	4,000	0,010	1,034	1,073
3	**M4a**	Future Islands	Ran	83	148	48950	0,006	0,644	7,306	106,000	0,005	0,465	0,504
4	**M5**	Wende	Au suivant	92	157	3560	0,005	0,459	7,121	20,000	0,010	0,957	0,996
5	**M6a**	Lucas Hamming	Be good or be gone (mi	87	152	790	0,002	0,180	6,842	7,000	0,004	0,372	0,411
6	**M8**	My Baby	Make a hundred	63	128	1630	0,002	0,190	6,852	15,000	0,006	0,638	0,677
7	**M9a**	The Homesick	St. Boniface	66	131	0	0,000	0,000	6,662	7,000	0,001	0,116	0,155
8	**M10**	The Elementary F	Wild Fever (minuut)	99	164	0	0,000	0,000	6,662	0,000	0,000	0,000	0,039
9	**M11**	Guus Meeuwis	Voor haar	16	81	6750	0,001	0,075	6,737	3,000	0,000	0,004	0,043
10	**M12a**	Delv!s	Come my way (minute)	66	131	1480	0,008	0,837	7,499	8,000	0,019	1,914	1,953
11	**M13a**	Linde Schöne	I'd Rather go blind	100	165	239800	0,002	0,220	6,882	129,000	0,001	0,122	0,161
12	**M15**	Pink Oculus	Touched by an angel	80	145	67	0,001	0,069	6,731	2,000	0,003	0,301	0,340
13	**M16**	Thijs Boontjes (&	Ballade van de moord	100	165	2730000	0,003	0,284	6,946	853,000	0,001	0,122	0,161
14		Roxeanne Hazes		25	90	704	0,003	0,268	6,930	0,000	0,000	0,000	0,039
15	**M17a**	Spoon	Hot thoughts	41	106	28570	0,006	0,598	7,260	73,000	0,006	0,573	0,612
16	**M18**	Michael Prins	The Heart of Life	87	152	153	0,000	0,026	6,688	-1,000	0,000	-0,039	0,000
17	**M19a**	Chef's Special	Try again (minute)	-1	64	10020	0,001	0,108	6,770	27,000	0,001	0,130	0,169
18	**M20a**	The Royal Engine	Hit it & do it again (min	100	165	894	0,001	0,138	6,800	1,000	0,001	0,112	0,151
19	**M22a**	Sue the Night	The big picture (minute	91	156	214	0,001	0,067	6,729	8,000	0,011	1,114	1,153
20	**M23**	Maaike Ouboter	Over de muur	91	156	883	0,001	0,072	6,734	2,000	0,001	0,054	0,093
21	**M24a**	Orange Skyline	Enemy	60	125	0	0,000	0,000	6,662	14,000	0,029	2,923	2,962
22	**M25**	Alex Roeka	De enkeling	77	142	9030	0,000	0,042	6,704	10,000	0,001	0,102	0,141
23	**M26a**	Paceshifters	Dead Eyes	100	165	179	0,001	0,088	6,750	4,000	0,007	0,680	0,719
24	**M27a**	Holly Macve	No one has the answer:	100	165	9960	0,002	0,173	6,835	17,000	0,002	0,215	0,254
25	**M29a**	45ACIDBABIES	Problems	100	165	0	0,000	0,000	6,662	0,000	0,000	0,000	0,039

Green: Searches

Orange: Views

Blue: Subcribers

Table 1.1. Explanation of how the index is calculated.

Column	Formula
Absolute	New - Old (number of searches, views or subs)
Relative	(New / Old) - 1
*100	[Relative] * 100
z-score	[Relative]* 100 + lowest value

Table 3.1

Multivariate analysis of variance (MANOVA).

Multivariate Tests[a]

Effect		Value	F	Hypothesis df	Error df	Sig.
Intercept	Pillai's Trace	,141	9,729[b]	3,000	178,000	,000
	Wilks' Lambda	,859	9,729[b]	3,000	178,000	,000
	Hotelling's Trace	,164	9,729[b]	3,000	178,000	,000
	Roy's Largest Root	,164	9,729[b]	3,000	178,000	,000
NumberPerformances1show1artist	Pillai's Trace	,038	2,368[b]	3,000	178,000	,072
	Wilks' Lambda	,962	2,368[b]	3,000	178,000	,072
	Hotelling's Trace	,040	2,368[b]	3,000	178,000	,072
	Roy's Largest Root	,040	2,368[b]	3,000	178,000	,072
Gender	Pillai's Trace	,013	,772[b]	3,000	178,000	,511
	Wilks' Lambda	,987	,772[b]	3,000	178,000	,511
	Hotelling's Trace	,013	,772[b]	3,000	178,000	,511
	Roy's Largest Root	,013	,772[b]	3,000	178,000	,511
Age	Pillai's Trace	,023	1,396[b]	3,000	178,000	,246
	Wilks' Lambda	,977	1,396[b]	3,000	178,000	,246
	Hotelling's Trace	,024	1,396[b]	3,000	178,000	,246
	Roy's Largest Root	,024	1,396[b]	3,000	178,000	,246
NewLanguage	Pillai's Trace	,035	2,145[b]	3,000	178,000	,096
	Wilks' Lambda	,965	2,145[b]	3,000	178,000	,096
	Hotelling's Trace	,036	2,145[b]	3,000	178,000	,096
	Roy's Largest Root	,036	2,145[b]	3,000	178,000	,096
NewNationality	Pillai's Trace	,052	3,248[b]	3,000	178,000	,023
	Wilks' Lambda	,948	3,248[b]	3,000	178,000	,023
	Hotelling's Trace	,055	3,248[b]	3,000	178,000	,023
	Roy's Largest Root	,055	3,248[b]	3,000	178,000	,023
NewGenre	Pillai's Trace	,017	1,017[b]	3,000	178,000	,386
	Wilks' Lambda	,983	1,017[b]	3,000	178,000	,386
	Hotelling's Trace	,017	1,017[b]	3,000	178,000	,386

	Roy's Largest Root	,017	1,017[b]	3,000	178,000	,386
NewGroupFormation	Pillai's Trace	,021	1,248[b]	3,000	178,000	,294
	Wilks' Lambda	,979	1,248[b]	3,000	178,000	,294
	Hotelling's Trace	,021	1,248[b]	3,000	178,000	,294
	Roy's Largest Root	,021	1,248[b]	3,000	178,000	,294
NewFame	Pillai's Trace	,053	3,344[b]	3,000	178,000	,020
	Wilks' Lambda	,947	3,344[b]	3,000	178,000	,020
	Hotelling's Trace	,056	3,344[b]	3,000	178,000	,020
	Roy's Largest Root	,056	3,344[b]	3,000	178,000	,020
Volume	Pillai's Trace	,006	,372[b]	3,000	178,000	,773
	Wilks' Lambda	,994	,372[b]	3,000	178,000	,773
	Hotelling's Trace	,006	,372[b]	3,000	178,000	,773
	Roy's Largest Root	,006	,372[b]	3,000	178,000	,773
Tempo	Pillai's Trace	,011	,635[b]	3,000	178,000	,593
	Wilks' Lambda	,989	,635[b]	3,000	178,000	,593
	Hotelling's Trace	,011	,635[b]	3,000	178,000	,593
	Roy's Largest Root	,011	,635[b]	3,000	178,000	,593
NewReactionPublic	Pillai's Trace	,022	1,317[b]	3,000	178,000	,270
	Wilks' Lambda	,978	1,317[b]	3,000	178,000	,270
	Hotelling's Trace	,022	1,317[b]	3,000	178,000	,270
	Roy's Largest Root	,022	1,317[b]	3,000	178,000	,270
NewPitch	Pillai's Trace	,035	2,135[b]	3,000	178,000	,097
	Wilks' Lambda	,965	2,135[b]	3,000	178,000	,097
	Hotelling's Trace	,036	2,135[b]	3,000	178,000	,097
	Roy's Largest Root	,036	2,135[b]	3,000	178,000	,097
NewSkinColour	Pillai's Trace	,049	3,052[b]	3,000	178,000	,030
	Wilks' Lambda	,951	3,052[b]	3,000	178,000	,030
	Hotelling's Trace	,051	3,052[b]	3,000	178,000	,030
	Roy's Largest Root	,051	3,052[b]	3,000	178,000	,030
Cover	Pillai's Trace	,035	2,136[b]	3,000	178,000	,097
	Wilks' Lambda	,965	2,136[b]	3,000	178,000	,097

	Hotelling's Trace	,036	2,136[b]	3,000	178,000	,097
	Roy's Largest Root	,036	2,136[b]	3,000	178,000	,097

a. Design: Intercept + NumberPerformances1show1artist + Gender + Age + NewLanguage + NewNationality + NewGenre + NewGroupFormation + NewFame + Volume + Tempo + NewReactionPublic + NewPitch + NewSkinColour + Cover

b. Exact statistic

Table 3.2

Tests of Between-Subjects effects

Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	z-score Searches	64474,968[a]	14	4605,355	4,076	,000
	z-score Views	1180,143[b]	14	84,296	,729	,743
	z-score Subcribers	31,327[c]	14	2,238	2,299	,006
Intercept	z-score Searches	32183,786	1	32183,786	28,484	,000
	z-score Views	183,721	1	183,721	1,590	,209
	z-score Subcribers	,038	1	,038	,039	,844
NumberPerformances1show1artist	z-score Searches	6487,115	1	6487,115	5,741	,018
	z-score Views	150,374	1	150,374	1,301	,256
	z-score Subcribers	,019	1	,019	,019	,890
Gender	z-score Searches	998,849	1	998,849	,884	,348
	z-score Views	137,822	1	137,822	1,192	,276
	z-score Subcribers	,023	1	,023	,024	,877
Age	z-score Searches	1555,748	1	1555,748	1,377	,242
	z-score Views	226,438	1	226,438	1,959	,163
	z-score Subcribers	1,180	1	1,180	1,213	,272
NewLanguage	z-score Searches	4474,865	1	4474,865	3,960	,048
	z-score Views	24,811	1	24,811	,215	,644
	z-score Subcribers	3,050	1	3,050	3,134	,078
NewNationality	z-score Searches	413,182	1	413,182	,366	,546
	z-score Views	197,005	1	197,005	1,704	,193
	z-score Subcribers	4,213	1	4,213	4,328	,039
NewGenre	z-score Searches	1008,939	1	1008,939	,893	,346
	z-score Views	192,243	1	192,243	1,663	,199
	z-score Subcribers	,739	1	,739	,760	,385

NewGroupFormation	z-score Searches	1265,378	1	1265,378	1,120	,291
	z-score Views	183,896	1	183,896	1,591	,209
	z-score Subcribers	,181	1	,181	,185	,667
NewFame	z-score Searches	11033,721	1	11033,721	9,765	,002
	z-score Views	27,525	1	27,525	,238	,626
	z-score Subcribers	,884	1	,884	,909	,342
Volume	z-score Searches	515,263	1	515,263	,456	,500
	z-score Views	8,937	1	8,937	,077	,781
	z-score Subcribers	,762	1	,762	,783	,378
Tempo	z-score Searches	1631,551	1	1631,551	1,444	,231
	z-score Views	39,677	1	39,677	,343	,559
	z-score Subcribers	,029	1	,029	,030	,863
NewReactionPublic	z-score Searches	3280,739	1	3280,739	2,904	,090
	z-score Views	,634	1	,634	,005	,941
	z-score Subcribers	,690	1	,690	,709	,401
NewPitch	z-score Searches	3323,115	1	3323,115	2,941	,088
	z-score Views	11,426	1	11,426	,099	,754
	z-score Subcribers	3,793	1	3,793	3,897	,050
NewSkinColour	z-score Searches	2641,980	1	2641,980	2,338	,128
	z-score Views	,836	1	,836	,007	,932
	z-score Subcribers	5,100	1	5,100	5,239	,023
Cover	z-score Searches	1537,015	1	1537,015	1,360	,245
	z-score Views	,301	1	,301	,003	,959
	z-score Subcribers	3,972	1	3,972	4,081	,045
Error	z-score Searches	203381,319	180	1129,896		
	z-score Views	20804,403	180	115,580		
	z-score Subcribers	175,215	180	,973		
Total	z-score Searches	3357883,000	195			
	z-score Views	34436,707	195			

	z-score Subcribers	265,595	195
Corrected Total	z-score Searches	267856,287	194
	z-score Views	21984,546	194
	z-score Subcribers	206,542	194

a. R Squared = ,241 (Adjusted R Squared = ,182)
b. R Squared = ,054 (Adjusted R Squared = -,020)
c. R Squared = ,152 (Adjusted R Squared = ,086)

Table 4.

Regression (ANOVA) model DV Views before eliminating outliers.

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1079,679	14	77,120	,698	,775[b]
	Residual	20988,095	190	110,464		
	Total	22067,775	204			

a. Dependent Variable: Normalized Views
b. Predictors: (Constant), Cover, NewReactionPublic, NewPitch, NewSkinColour, NewFame, Volume, NewGroupFormation, Age, Number of Performances in 1 show by 1 artist, Gender, Genre, Tempo, NewLanguage, NewNationality

Graph 1.

Scatterplot for testing homoscedasticity on DV Views (z-score).

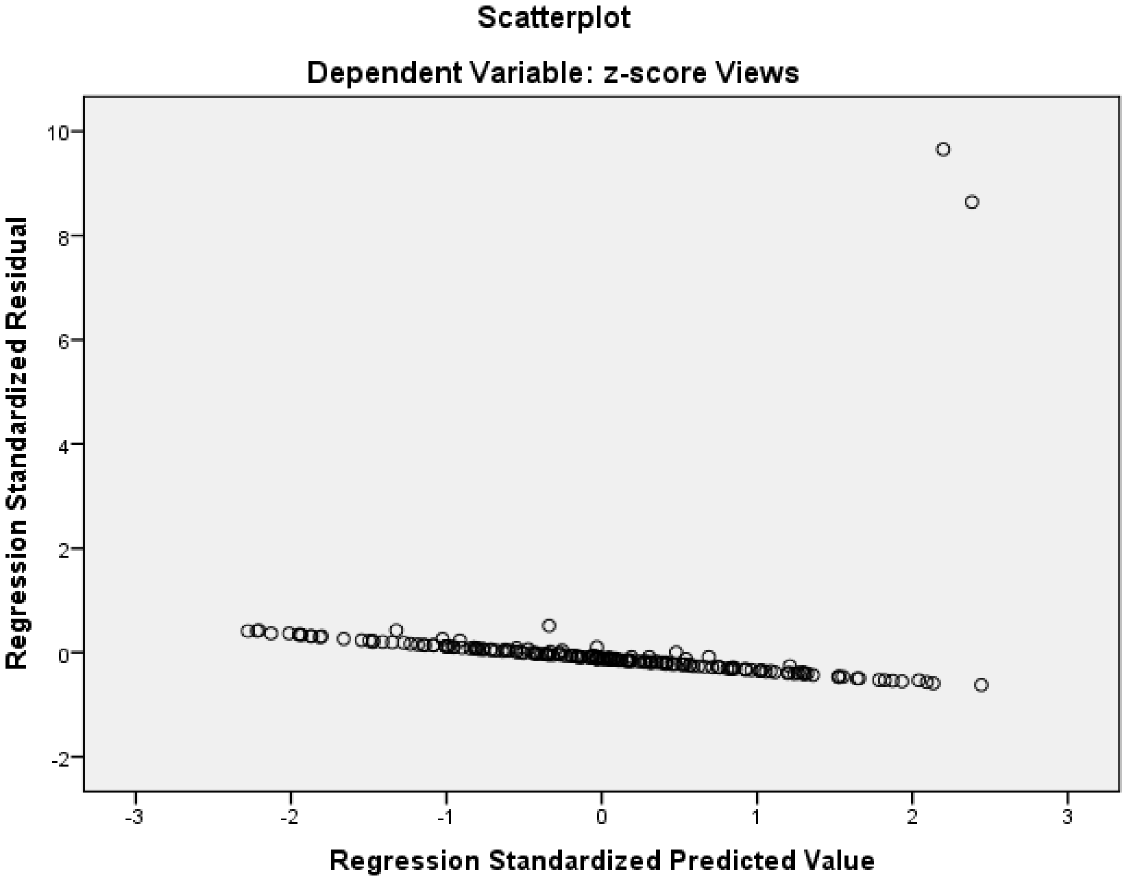

Table 5.

Mean of Absolute number of extra views after DWDD compared to mean of average extra views a day.

Report

	Average daily extra views	Absolute number of views
Mean	5827,694	85222,398
N	196	196
Std.	879950,393	251146,984
Deviation	2	7

Table 6.

Regression model for DV Searches (with all IV's).

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	87,015	16,304		5,337	,000
	Number of Performances	7,071	2,951	,175	2,396	,018
	Gender	-1,207	1,283	-,067	-,940	,348
	Age	5,007	4,267	,083	1,173	,242
	NewLanguage	12,995	6,530	,158	1,990	,048
	NewNationality	4,745	7,847	,056	,605	,546
	NewGenre	5,620	5,947	,072	,945	,346
	NewGroupFormation	-5,684	5,371	-,077	-1,058	,291
	NewFame	19,633	6,283	,237	3,125	,002
	Volume	-2,525	3,739	-,049	-,675	,500
	Tempo	-3,430	2,854	-,092	-1,202	,231
	NewReactionPublic	3,065	1,799	,115	1,704	,090
	NewPitch	3,763	2,194	,120	1,715	,088
	NewSkinColour	-10,705	7,001	-,137	-1,529	,128
	Cover	-7,211	6,183	-,088	-1,166	,245

a. Dependent Variable: z-score Searches

Table 7.

Regression model for DV Subscribers (with all IV's).

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	,094	,479		,197	,844
	Number of Performances in 1 show by 1 artist	-,012	,087	-,011	-,138	,890
	Gender	,006	,038	,012	,155	,877
	Age	-,138	,125	-,083	-1,101	,272
	NewLanguage	,339	,192	,148	1,770	,078
	NewNationality	-,479	,230	-,202	-2,080	,039
	NewGenre	-,152	,175	-,070	-,872	,385
	NewGroupFormation	-,068	,158	-,033	-,431	,667
	NewFame	,176	,184	,076	,953	,342
	Volume	-,097	,110	-,068	-,885	,378
	Tempo	,014	,084	,014	,173	,863
	NewReactionPublic	-,044	,053	-,060	-,842	,401
	NewPitch	,127	,064	,146	1,974	,050
	NewSkinColour	,470	,205	,216	2,289	,023
	Cover	,367	,181	,161	2,020	,045

a. Dependent Variable: z-score Subcribers

Table 8.

Frequency table Gender.

Gender

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Female	46	23,5	23,5	23,5
	Equally mixed	13	6,6	6,6	30,1
	Bigger part male	18	9,2	9,2	39,3
	Male	119	60,7	60,7	100,0
	Total	196	100,0	100,0	

Table 9.

Frequency table Age.

Age

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	< 18	3	1,5	1,5	1,5
	18 - 30	94	48,0	48,0	49,5
	31 - 50	88	44,9	44,9	94,4
	> 50	11	5,6	5,6	100,0
	Total	196	100,0	100,0	

Table 10.

Frequency table Language of Performance.

Language of performance

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Dutch	56	28,6	28,6	28,6
	English	115	58,7	58,7	87,2
	Other Eurpean	4	2,0	2,0	89,3
	Exotic (non-European)	4	2,0	2,0	91,3
	Other	1	,5	,5	91,8
	No Singing	14	7,1	7,1	99,0
	Mixed	2	1,0	1,0	100,0
	Total	196	100,0	100,0	

Table 11.

Frequency table Nationality.

Nationality

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Dutch	125	63,8	63,8	63,8
	European (non-Dutch)	22	11,2	11,2	75,0
	American	6	3,1	3,1	78,1
	Exotic	34	17,3	17,3	95,4
	Other	9	4,6	4,6	100,0
	Total	196	100,0	100,0	

Table 12.

Frequency table Group Formation.

Group Formation

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Solo artist	40	20,4	20,4	20,4
	Solo but backed up with musicians	58	29,6	29,6	50,0
	Classical band	45	23,0	23,0	73,0
	Band + copper instruments	8	4,1	4,1	77,0
	Orchestra	3	1,5	1,5	78,6
	Other	4	2,0	2,0	80,6
	Duo or Trio (with or without back up music)	37	18,9	18,9	99,5
	Total	196	100,0	100,0	

Table 13.

Frequency table Skin Colour.

Skin Colour

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	White	130	66,3	66,3	66,3
	Black	35	17,9	17,9	84,2
	Mixed race	17	8,7	8,7	92,9
	Mixed within band	14	7,1	7,1	100,0
	Total	196	100,0	100,0	

Table 14.

Descriptive statistics and correlations between all IV's and DV's.

Descriptive Statistics & Correlations[c,d]

	N	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1 z-score Searches	196	125,571	37,3167	1,000																
2 z-score Views	196	7,98491	10,618320	.106	1															
3 z-score Subcribers	196	,54812	1,029622	.163*	.373**	1														
4 Number of Performances	196	2,061	,9206	.198**	.101	.101	1													
5 Gender	196	3,60	2,072	-.171*	.061	-.063	-.041	1												
6 Age	196	1,55	,627	.012	-.096	-.177*	.013	.014	1											
7 NewLanguage	196	,7143	,45291	.320**	.072	.186**	.239**	-.051	-.170*	1										
8 NewNationality	196	,2500	,43412	-.092	.051	-.103	-.064	-.031	.024	-.130	1									
9 NewGenre	196	,6531	,47722	-.037	-.037	-.047	.084	.160*	-.135	.132	.248**	1								
10 NewGroupFormation	195	,4974	,50128	-.065	.097	.033	.196**	.214**	-.037	.145*	-.151*	.211**	1							
11 NewFame	196	,7245	,44792	.293**	.065	.195**	.054	-.135	-.229**	.419**	-.066	.030	-.003	1						
12 Volume	196	2,15	,721	-.091	-.023	-.078	.001	.165*	-.038	.040	.057	.289**	.151*	.004	1					
13 Tempo	196	2,03	1,000	-.116	-.005	.035	.087	.114	-.252**	.095	.198**	.341**	,144*	.096	.329**	1				
14 NewReactionPublic	196	1,6582	1,39981	.104	-.009	-.004	-.131	-.118	-.020	.072	-.044	-.132	-.031	.021	-.090	-.049	1			
15 NewPitch	196	3,0408	1,18467	.191**	.045	.196**	.148*	-.234**	-.106	.108	-.130	-.138	.035	.099	.029	-.105	.046	1		
16 NewSkinColour	196	,3367	,47380	-.119	.033	.060	.011	-.114	-.052	-.075	.661**	.202**	-.040	-.044	-.017	.198**	.043	-.070	1	
17 Cover	196	,71	,453	-.077	.064	.163*	.251**	.108	-.188**	-.075	.078	.180*	.223**	.141*	.025	.243**	.007	.051	.068	1
Valid N (listwise)	195																			

c. * Correlation is significant at the 0.05 level (2-tailed)

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