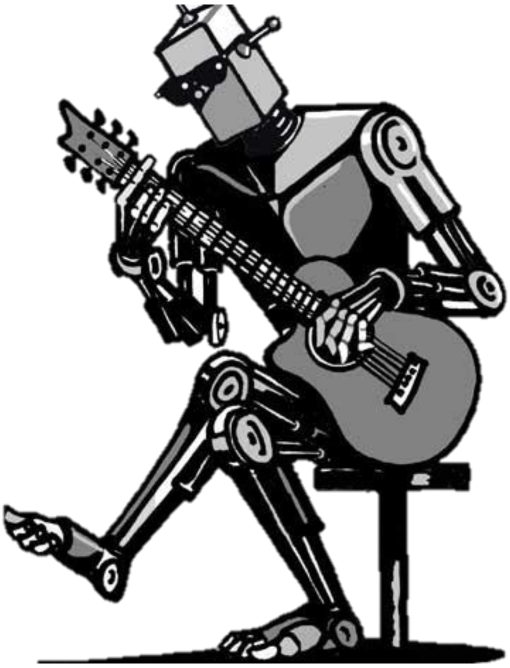

Figure 1 Robot Musician (Schmidhuber 2006)

The 'Human-Creativity Effect': a Major Drawback of Big Data Usage in New Product Development

Thesis

To obtain the academic degree of Master of Science in Economics & Business
(Major in Marketing)

ERASMUS UNIVERSITEIT ROTTERDAM
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Abstract

Big data is more and more used in the development of new products, because it offers several benefits. For example, in new product development, the use of big data analysis (BDA) leads to more successful products. However, before the use of BDA, new products were developed solely by human creativity. This (partial) replacement results in a major drawback of the big data usage. In this paper, I present a first finding of the human-creativity effect: the tendency of consumers to perceive a product as more attractive when it is created solely with human creativity than when it is created with the help of BDA. This effect is partly driven by the perception that products created by humans contain love, which is injected in these products by the creator. Moreover, I find that the use of BDA in the new product development leads to higher privacy concerns. Furthermore, I find that currently the usage of solely human creativity is still seen as the default production mode of new products. My research is based on an experiment on students in The Netherlands, in which these students listened to a piece of a song and evaluated this song afterwards.

Acknowledgements

Utrecht, 2018

Dear reader,

This master thesis has been done as part of the MSc in Economics and Business, Marketing track, at the Erasmus School of Economics, Erasmus University Rotterdam. Because the process of writing this thesis was long and intensive, I want to take this opportunity to thank some people who had an impact on this process. Without them, this thesis would not have become as what it is now.

First of all, I like to express my gratitude towards my thesis advisor Nuno Almeida Camacho. Thank you for directing me to the interesting and important topic of big data usage in the music industry. Your enthusiasm, thinking along and your interest in my research gave my motivation a boost. Furthermore, I want to thank you for your fast and extensive feedback. I appreciate all your help, which enabled me to write the thesis as it stands.

Besides, I would also like to thank my co-reader Gert Jan Prevo for reading my thesis and thereby taking part of the thesis process as well.

Furthermore, I would like to thank everyone who responded to my survey and thereby participated in the experiment. It would have been difficult to write this thesis without your responses and help.

In addition, I would like to thank Stefan and Alice. I appreciate the feedback you gave on parts of my thesis. Likewise, I must express gratitude to my girlfriend Sietske. In addition to the feedback you gave, you always motivated and supported me. Furthermore, I would like to thank Irene. I enjoyed writing our theses together, and all the coffee and talks in between. Furthermore, I want to thank my parents. You always supported me, both during the thesis process and during my time at the university. Finally, I am grateful that I have been given the ability and possibility to study and write this master thesis.

Gertjan Bos

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List of Abbreviations

ANOVA	Analysis of Variance
ANCOVA	Analysis of Covariance
AVE	Average Variance Explained
A&R	Artist and Repertoire
B	Coefficient
BC	Bias Corrected
BCa	Bias Corrected an Accelerated
BDA	Big Data Analysis
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index
CI	Confidence Interval
Corr.	Correlation
F	F-statistic for AN(C)OVA and Levene's Test
GDP	Gross Domestic Product
M	Mean
N	Number
NFI	Normed Fit Index
NPD	New Product Development
Ns	Not Significant
Obs.	Observations
P	P-level, level of significance
Perc.	Percentile
RMSEA	Root Mean Square Error of Approximation
SD	Standard Deviation
SE	Standard Error
SEM	Structural Equation Modelling
Sig.	Significance
SRMR	Standardized Root Mean square Residual
TLI	Tucker-Lewis Index
TMA	Traditional Marketing Analytics
WTP	Willingness To Pay
Z	Z-statistic for Bootstrapping Analysis

1. Introduction

1.1. Context of the Research and Problem Definition

Nowadays, big data plays a crucial role in company decision making. Big data is often described as datasets that cannot be managed, analyzed, stored and captured by traditional software tools (Manyika et al. 2011). Marketers can rely on big data to find data patterns that uncover valuable insights about consumer behavior, which they can use to get market advantage (Erevelles et al. 2016). Xu et al. (2016) state that consumer insights, generated by big data, help marketers increase the odds of success of their new product development efforts. Especially relevant is the role of big data as a new source for idea generation (Manyika et al. 2011). An example of this is Netflix that used big data in content generation for making key decisions on how to build their hit series House of Cards (Petraetis 2017). Netflix used big data to research customer preferences. This type of big data usage is part of their product development approach, which focuses on satisfying its customers (The Netflix Technology Blog 2011).

Big data is used in other creative industries as well. For example, in the music industry several start-ups promise to help musicians compose songs with the help of big data. One example is the Spanish company Polyphonic HMI [1] that tries to find mathematical patterns in popular songs with their HSS program (Witchalls 2004). HSS stands for Hit Song Science. This name already indicates that Polyphonic focuses on the use of big data to transform the composition of songs from an art into a science. First of all, HSS splits songs on several construction aspects, like beat, tempo, pitch, melody and harmony (Tatchell 2005). These aspects are used to indicate mathematical patterns in new songs. Thereafter, HSS matches these patterns against a database of hit singles and thereby HSS predicts the likelihood of the song's success. Big record labels use the HSS program, to test and predict the success of their new songs. Furthermore, the HSS program advises how the song, or certain construction aspects, can be tweaked, in order to increase the likelihood of its success (Mike 2005). Another example of big data usage in music composition comes from Augur (2016), who states that big data is used to create rhythms and rhythm fluctuations, for example by 'Data-Driven-DJ'. This producer uses data from interesting issues, like Beijing's smog and air quality data or data on global refugees, to create sounds and compose songs. Another illustration of the use of big data is described by Marr (2017): musicians that use the IBM program

[1] Human Media Interface

BEAT, which is a machine-learning-driven music generating algorithm that creates recorded music.

Despite all its benefits, there are three potential drawbacks associated with the use of big data analysis in new product development, especially in creative industries. These drawbacks arise because before the use of big data, new content was created solely by human creativity. This change in how content is created causes people to doubt if products created with the help of big data analysis are creative and artistic as well (Amabile 1983; PromptCloud 2017). This is important for firms, as prior research indicates that customers care not only about the ultimate products, but also about how it was created in the first place. For example, Fuchs et al. (2010) find that consumers that are empowered to select products in the new product development process, are having a higher purchase intention and willingness to pay for that product than consumers that are not empowered in the production process. Another example of such an effect is the *handmade-effect*, which states that products labeled as handmade are seen as more attractive than exactly the same products that are labeled as machine-made, because handmade products contain more love (Fuchs et al. 2015). These effects show that when customers evaluate a product or service, they value not only the output but the production process as well. One can expect a similar effect to arise when firms use big data analysis, instead of human creativity, in new product development. I label such effect as the *human-creativity effect,* i.e. the tendency of consumers of creative products, such as movies, songs or video games, to perceive a product as more attractive when it is created solely with human creativity than when it is created with the help of big data analysis.

This human-creativity effect could be driven by the following three drawbacks of big data analysis. First, consumers may value human creativity over big data analysis, because they perceive products to be more creative if they are produced solely by human creativity than based on outcomes of an algorithmic process (Amabile 1983). Second, consumers may value human creativity, because human creators tend to express emotions like love and passion into the products they create, and they believe big data analysis is not able to do so (Fuchs et al. 2015). Third, consumers may have privacy concerns regarding big data and may perceive the privacy costs related with the creation of such content as too high to justify the benefits (Phelps et al. 2000; Wedel and Kannan 2016). These drawbacks show that consumers are concerned with *how* the product (*what)* is produced and by *whom*. Hence, the research problem in this paper is: *although* *big data has many positive influences in new product development, its use could be a reason consumers value the product less than when it is made solely by human creativity.*

1.2. Academic and Managerial Relevance

This research problem is important in our more and more data driven society, because marketing managers need to serve customers and give them the highest value possible. If the production process has an influence on the customer value of that product, then managers need to take this into account. Moreover, if the possible drawbacks associated with the use of big data analysis exist, then managers probably should be conservative with the use of big data analysis and maybe use human creativity instead. At the same time, if the effect is not present and is simply a misguided fear, then firms can proceed more confidently towards the adoption of big data in their creative efforts. These insights are especially important to the creative industries[2], where it applies to the successful launch of new content, which the Netflix example showed. Consequently, if the product development process has an influence on consumer's value perceptions over and above the output content per se, content companies need to take this into account to serve the customer in the best way possible.

Current literature on the influence of the product development process on customer product perception in new product development focuses on co-creation: customer influences in the development process. Fuchs et al. (2010) found that consumers have higher demand for a product when they were empowered to select the products to be marketed. Furthermore, there is a mediating effect of perceived consumer control on the pleasantness of service experience (Hui and Bateson 1991). Beside the literature on co-creation, Fuchs et al. (2015) found that products produced by machines are perceived as less attractive and valuable than human-made products, because these contain less love. Yet, no research that I am aware of has been done on other factors of the development process that may influence the consumer product value perception, namely the (non-)usage of big data during the early-stage of new product development, i.e. the idea creation phase.

This study offers a first attempt to find if the partial replacement of human creativity, by big data analysis, in new product development influences consumer's

[2] This industry consists of several segments, like movies, video games and music. Moreover, it consists of upcoming segments as e-sports and virtual reality. In 2017 the global revenue for the industry was 1.9 trillion US$, which is expected to rise to 2.4 trillion US$ by 2022 (PwC 2018).

product value perceptions. I test my theory-driven hypotheses using an online survey experiment. Students (N = 229, M_{age} = 22, 56% female) were randomly assigned to one of three experimental treatments before listening to the exact same song. They were briefed that the new song they were about to listen to is either (1) made with the help of *big data analysis*, (2) solely made by *human creativity*, or they belonged to (3) a *control group* that received no information on how the song was developed. After listening to the song, students were asked to value the song on perceived creativity and value perceptions. With this approach, this paper makes the following contributions to the new product value perception literature:

First, this paper is the first to empirically examine whether or not the human-creativity effect is present and significant for firms, i.e., whether consumers perceive the same product differently if told that it has been designed with big data versus human creativity. Second, I explore the mechanisms through which the human-creativity effect arises. Specifically, perceived *creativity*, *love* and *privacy concerns* are proposed as mediators for the human-creativity effect. Third, this paper explores these questions in the context of creative industries. Despite representing $1.9 trillion per year in value (PwC 2018), the creative industries have been somewhat neglected in the new product development literature in marketing. Thus, this paper delves into the institutional context of the music industry to ensure in-depth and managerially-relevant results and implications from my findings.

1.3. Structure of the Thesis

This section gives an overview on the paper's structure. First of all, in the second chapter I define the main concepts of human creativity and big data analysis, and review existing literature on the direct role of these concepts in new product development. Furthermore, in the third chapter I provide the institutional context of the creative industries, with a focus on the music industry. Thereafter, in chapter four, I substantiate hypotheses with literature of various streams and summarize these in the conceptual framework. Moreover, in the fifth chapter I explain the methods on how I test these hypotheses. Thereafter, in the sixth chapter I analyze the data and give results. Finally, in the seventh chapter I discuss the outcomes, state conclusions, show the academic contribution and managerial implications and outline limitations and directions for future research.

2. Literature review: Direct Effects of Human Creativity and BDA in NPD

In this chapter, I define the constructs of human creativity and big data analysis (BDA) and review the literature on the direct influence of both in the new product development process. Therefore, I firstly describe the new product development process.

2.1. New Product Development Process

Over the years, extensive research has been done on new product development (NPD), which is the first phase of the product life cycle (Klepper 1996). The wide interest in NPD comes from the fact that the success of new products is crucial for companies and for its creators. Moreover, it is essential for the success, survival and renewal of organizations (Brown and Eisenhardt 1995). Therefore, most of the research focuses on the success and failures of new products, looking at the reasons behind the success or failure. Cooper (1979) states three keys to new product success: (1) product uniqueness and superiority, (2) market knowledge and marketing competence and (3) technical and production synergy and skills. Sethi et al. (2001) describe this first key to success as: "a primary determinant of new product success is the extent to which the product is different from competing alternatives in a way that is valued by customers". Andrews and Smith (1996) refer to this as the innovativeness of a product, which they describe as the uniqueness and meaningfulness of a product.

Because research on NPD is so extensive, the process of NPD is divided into several stages. Ernst et al. (2010) summarize all possible stages into three overlapping stages: (1) concept development, (2) product development and (3) implementation. In this research I focus on the concept development stage, because BDA and human creativity have the most influence in this stage, which is shown in the following subchapters. The concept development stage consists of the following parts: generation of ideas, selection of product ideas, determination of product features and analyzation of market trends, changes and potential (Ernst et al. 2010).

2.2. Creativity in New Product Development

Now I will discuss creativity. Creativity has been researched extensively in the context of marketing, but also in the fields of psychology and organizational behavior. There has been much discussion on the definition of creativity in past literature, especially in the context of innovation. A summary on this discussion, and the most important papers in literature on creativity, is provided in Table 1.

According to Amabile (1988), definitions of creativity in past research can be divided into three categories: (1) *person* definitions, (2) *process* definitions and (3) and *product* definitions. The first definition focuses on the creativity of *who* the product created, the second on the process of *how* the product is created and the third definition on *what* product is created. It is difficult to measure the creativity of a person (personal characteristics), because this only can be done by a professional jury. Furthermore, it is hard to measure how creative a process is (Amabile 1983). Therefore, researchers most often use the product definition, as it is the easiest to measure. According to the product definition, *creativity* is defined as the production of useful and novel ideas (Amabile 1982, 1983; Amabile et al. 1996; Mumford and Gustafson 1988; Woodman et al. 1993). Thus, the creativity of a product *(what)* can be measured by evaluating that product on novelty and usefulness.

Over the years, several researchers have clarified important aspects of this definition of creativity. First of all, the presence of both novelty and usefulness is important, because a novel idea that is not useful to customers is seen as bizarre (Im and Workman 2004). Furthermore, a product is regarded novel if it is totally new or a significant recombination of existing products (Oldham and Cummings 1996). In addition, this novelty should be measured in what it means to the consumer and to their view on the product, instead of the new physical state of the product (Shaw 1965; Wasson 1960). Furthermore, creativity is a continuous concept, which means that products have a certain level of creativity, instead of being either a creative product or a non-creative product (Perry-Smith and Shalley 2003). In this continuous concept, a recombination of existing products is seen as a minor contribution and groundbreaking new ideas are seen as major contributions of creativity (Mumford and Gustafson 1988).

According to Amabile et al. (1996), creativity can originate from both individual humans and teams. Both together are seen as the seed of all innovation. *Innovation* is defined as: the production of creative ideas and the implementation of these ideas (Amabile et al. 1996; Scott and Bruce 1994). In research on creativity in NPD, Im and Workman (2004) state that creativity positively influences NPD success by the innovativeness it entails. In this effect of creativity on NPD success, Im and Workman (2004) found a higher influence of the product's usefulness than the product's novelty. In the NPD stages of Ernst et al. (2010) innovation is especially important in the concept development stage, because the innovativeness of products is one of Cooper's (1979) key drivers for product success (Andrews and Smith 1996). Furthermore, Cooper

(1979) found that highly innovative products are unique and superior, which leads to the success of new product. The opposite effect exists as well, indicated by Crawford (1977), who states that a lack of innovativeness is an important reason for products to fail. Moreover, Sethi et al. (2001) describe the role of creativity in the concept development stage, and state that creativity is needed in the processes of product ideation and design in order to be innovative.

The concepts of creativity and innovation are so intertwined, that these concepts have even been treated as synonyms in past literature, even though we know they are not the same (Scott and Bruce 1994). This confusion arises because creativity is such a crucial element in innovation. All in all, creativity of individuals is an important factor in innovation and idea generation in (the concept development stage of) NPD, thereby human creativity contributes to the success of new products.

Table 1 Important Studies on Creativity

Author(s)	Journal	Main focus	Definition of creativity	Important findings
Amabile (1982)	Journal of Personality and Social Psychology	Social psychology of creativity.	Creative products are novel (unusual, statistical infrequent or completely unique) and appropriate (correct in the context it was addressed to).	They develop a reliable subjective assessment technique based on the creativity definition, including examples, limitations and advantages.
Amabile (1983)	Journal of Personality and Social Psychology	Social psychology of creativity.	The product definition of creativity: its novelty and usefulness, is preferred over the creative process/ person definition by researchers.	A componential framework for conceptualizing creativity is presented in a cognitive-abilities approach.
Amabile (1988)	Research in Organizational behaviour (5843 cit.)	Influence of creativity in organizations.	The product-oriented definition: “novelty that is useful” is chosen over the process and person definitions.	Develops a model of individual creativity and integrates it in an existing model of organizational innovation.
Amabile et al. (1996)	The Academy of Management Journal	Creativity in organizational environments.	The production of novel and useful ideas in any domain.	Development of the KEYS-tool: determine perceptions of important work environment dimensions of creativity.
Besemer and O’Quin (1986)	The Journal of Creative Behavior	Scale to assess the creativity of products.	Besemer and Treffinger’s (1981) three dimensions: Novelty, Resolution and Elaboration & Synthesis.	Create Creative Product Semantic Scale to do an experiment and analysis on perceived consumer creativity.
Besemer and Treffinger (1981)	The Journal of Creative Behavior	Criteria to assess the creativity of products	Extension of Jackson and Messick’s (1965) response properties. Define three dimension categories: Novelty, Resolution and Elaboration & Synthesis.	Create a framework based on the three categories, including properties.
Besemer (1998)	Creativity Research Journal	Scale to assess the creativity of products.	Besemer and Treffinger’s (1981) three dimensions: Novelty, Resolution and Elaboration & Synthesis.	Shows that factor analysis find three factors for creativity: Novelty, Resolution (meaningful) and an aesthetic/stylistic one.

Table 1 continued: Important Studies on Creativity

Author(s)	Journal	Main focus	Definition of creativity	Important findings
Im and Workman (2004)	Journal of Marketing	The role of new product and marketing program creativity.	Consistent with Amabile (1983), the 'output perspective': unique differences and meaningfulness are two dimensions of creativity.	New product creativity and marketing program creativity mediates the relationship between market orientation and new product success.
Jackson and Messick (1965)	Journal of personality	Develop a scheme to evaluate creativity.	The product definition of creativity is consisting of: the unusualness (novelty), appropriateness (meaningful/useful), transformation (radical unusualness) and condensation.	Propose judgmental standards corresponding to the response properties to creativity and state aesthetic responses to these properties.
Mumford and Gustafson (1988)	Psychological Bulletin	The description/ understanding of creative behavior.	Define creativity in terms of novel, socially valued products (product definition).	Develop a syndrome conceptualization of creativity including stages of ideation, process, setting and outcomes.
Oldham and Cummings (1996)	The Academy of Management Journal	Employee creativity characteristics/ performance.	Products that are novel or original and potentially relevant ore useful (product definition).	Employees produce more creative products if they have creative-relevant characteristics, a challenging job and are supportive supervised.
Perry-Smith and Shalley (2003)	The Academy of Management Review	Individual creativity and social relationships.	Creativity leads to the generation of novel and appropriate ideas (product definition).	Present an individual creativity life cycle model in network position terms.
Scott and Bruce (1994)	The Academy of Management Journal	Determinants of individual innovative behavior.	Terms of creativity and innovation use interchangeable. Creativity is the production of novel and useful ideas (product definition).	Develop and test a model of individual innovative behavior.
Sethi et al. (2001)	Journal of Marketing Research	Influence of development teams on the creativity of the new product.	Use creativity and innovation interchangeable and describe an innovative outcome as novel and appropriate, citing papers on creativity.	Found that the creativity/innovativeness of new products is related to the context and team characteristics.
Woodman et al. (1993)	The Academy of Management Review	Organization-al creativity.	Creativity is the creation of a valuable, new product (product definition).	Develop an interactional framework for organizational creativity.

2.3. Big Data Analysis in New Product Development

In this subchapter, I discuss *Big data analysis* (BDA), which is the analysis of big data. *Big data* is often described as datasets that cannot be managed, analyzed, stored and captured by traditional software tools (Manyika et al. 2011). These tools help find hidden patterns in data, which is called *data analytics* (Erevelles et al. 2016). Thus, BDA is about the use of tools that help find these hidden patterns in *big data*. Therefore, big data and analytics are paired together. The tools that are used for BDA are data mining algorithms and statistical analyses like: regression, clustering, classification, association and network analysis (Chen et al. 2012).

However, researchers still debate on how to define *big data*. Therefore, most researchers describe big data by its characteristics: The four V's of volume, velocity, variety and veracity (Wedel and Kannan 2016). First, (1) the *volume* characteristic of big data indicates that the magnitude of the data is too large to handle in traditional procedures. Second, (2) the *velocity* characteristic indicates the ruthless speed of which this data is generated with. Third, (3) the *variety* characteristic indicates the combination of various types of structured and unstructured data. Fourth, (4) the *veracity* characteristic indicates the awareness that big data is not always accurate, which harms the quality of outcomes (Erevelles et al. 2016; Wedel and Kannan 2016). According to Wedel and Kannan (2016), researchers sometimes add a fifth V: the *value* characteristic, which indicates "the low density and the high overall value of Big Data" (Li et al. 2015). Yet, this seems like an output characteristic that is at a different level of generality than the remaining four V's. A summary on the big data characteristics discussion, and the most important papers on BDA, is shown in Table 2. In this research, I use the four V's to describe big data and define *big data analysis (BDA)* as the use of tools to find hidden patterns in big datasets.

Before the availability of big data, researchers used *traditional marketing analytics* (TMA) in NPD (Xu et al. 2016). TMA is done with small data sets, often executed by company managers and used in company decision making. However, TMA is not able to manage big datasets, because it is either too voluminous or too unstructured (Davenport et al. 2012). Therefore, TMA can be seen as analytics that can be used to find patterns in small datasets with lower *volume*, *variety*, *velocity* and *veracity* (Xu et al. 2016). Another difference between TMA and BDA, is BDA's use of real-time data. Furthermore, BDA gives the ability to monitor consumers and the market more closely than that is possible with TMA. Moreover, BDA reduces the costs of this monitoring. However, despite its decreasing role, TMA can still facilitate new product success (Xu et al. 2016). Besides, BDA and TMA can be used together in NPD, although some types of information and data require BDA (Xu et al. 2016).

Recent studies have further examined the role of big data in NPD. Li et al. (2015) found that BDA has a positive effect on the whole product life cycle. More specifically, according to Manyika et al. (2011), BDA in general helps companies to create new products. An example of this, is that BDA can help create products that consumers are more willing to buy (Xu et al. 2016).

Table 2 Important Studies on Big Data

Author(s)	Journal	Main focus	Characteristics of big data	Important findings
Chen et al. (2012)	Mis Quarterly	Overview on business intelligence and analytics.	Volume, Velocity & Variety.	An overview on business intelligence and analytics: evolution, application and emerging research areas.
Davenport et al. (2012)	MIT Sloan Management Review	Difference between big data and traditional analytics.	Do not name big data characteristics.	Difference for BDA is monitoring a flow of data instead of a fixed supply, work of data scientists instead of analyst and integrate it in core business.
Erevelles et al. (2016)	Journal of Business Research	Impact of big data on marketing.	Volume, Velocity, Variety, Value & Veracity.	Propose a conceptual framework on the impact of big data on marketing activities, based on resource-based theory.
Fosso Wamba et al. (2016)	International Journal of Production Economics	Value of big data for businesses.	Volume, Velocity, Variety, Value & veracity.	Provide a conceptual framework for classification of big data related articles.
Kshetri (2014)	Telecommunications Policy	Organization’s costs, benefits and externalities in big data usage.	Volume, Velocity, Variety, Variability & Complexity.	Owning and storing risks increase with size, variety and complexity of data. Big data use creates privacy concerns.
LaValle et al. (2011)	MIT Sloan Management Review	How organizations use analytics to gain insight.	Do not name big data characteristics.	Managerial and cultural challenges most important in adopting analytics.
Li et al. (2015)	International Journal of Advanced Manufacturing Technology	Big data in product life cycle management.	Volume, Velocity, Variety, Value & Variability.	Summarize existing applications of big data in product life cycle management and investigate potential applications.
Lycett (2013)	European Journal of Information Systems	Value delivering of data analytics.	Volume, Velocity, Variety & Value.	Datafication creates value in three ways: dematerialization, liquidity and density.
Manyika et al. (2011)	McKinsey Global Institute	Value of big data for organizations and economic sectors.	Do not name big data characteristics.	Tries to identify, qualify and illustrate the potential value that big data can create for organizations and sectors.
Wedel and Kannan (2016)	Journal of Marketing	Marketing analytical methods for big data environments.	Volume, Velocity, Variety, Veracity & Value.	Identify directions for new analytical research methods.
Xu et al. (2016)	Journal of Business Research	Big data and traditional analytics in new product success	Volume, Velocity, Variety &Veracity.	Big data and traditional analysis both positively influence new product success. When combined, they can contribute to new ideas and innovations.

As discussed in the introduction, BDA is important in the concept development stage of Ernst et al.'s (2010) NPD stages. In this stage, BDA in general positively influences NPD and design (Li et al. 2015; Xu et al. 2016). Moreover, BDA is seen as a driver in innovation (Lycett 2013; Manyika et al. 2011). Furthermore, big data is a new source of idea generation (Erevelles et al. 2016; Manyika et al. 2011), thereby (partly) replacing human creativity as the source of the idea. Besides, with the help of big data, the creative and innovative process can be improved and the speed of idea generation increased (Erevelles et al. 2016). In this manner it works complementary to human creativity. Finally, BDA is used for market research in the concept development stage as well (Xu et al. 2016). In conclusion, BDA is an important factor in innovation and idea generation in NPD, especially in the concept development stage, and thereby BDA contributes to the success of new products. Moreover, BDA can be used complementary to human creativity or instead of human creativity in idea generation and the creative process.

3. Institutional Context

This chapter gives an overview of the creative industries with an extra focus on the music industry, since the product I do research on is a pre-recorded piece of a song. Therefore, I look into the creative process of composing new songs and the role of human creativity and BDA in this process.

The *creative industries* can be defined as industries containing “activities which have their origin in individual creativity, skill and talent and which have the potential for wealth and job creation through generation and exploitation of intellectual property” and include sectors like: music, films, video and computer games, television, radio, arts, advertising, architecture, etcetera (Cunningham 2002). Besides their contribution to society and culture, the creative industries contribute to economic growth and development as well. In this way the creative industries can be an economic growth stimulator (Potts and Cunningham 2008). The contribution of creative industries to the global economy in terms of revenues is $1.9 trillion annually (PwC 2018). According to World Creative (2017), in 2015 the creative industries revenues were 3% of the global GDP and 29.5 million people had a job in these industries. Another important issue in the creative industries is that producers are identified as artists (Garnham 2005). Artist are “those who create primarily to express their subjective conceptions of beauty, emotion or some other aesthetic ideal” (Hirschman 1983).

One of the creative industries is the *music industry*. The music industry is more labor intensive and artisanal than most of the other creative industries (Flew and Cunningham 2010). Moreover, the music industry is one of the creative industries that is partly commercialized. Including radio and podcasts, the global music industry revenues were $94.9 billion in 2017. This is expected to increase to $113.4 billion by 2022 (PwC 2018). According to World Creative (2017), in 2015 almost 4 million people were employed in the global music industry. Therefore, the global music industry is important in terms of both global GDP and employment.

Furthermore, the music industry is one of the creative industries that produces digital content (Cunningham 2002). The music industry can be viewed from different levels: record companies and bands or artists (Cameron and Collins 1997). Most papers focus on popular music, which: “involves a deliberate intention to manufacture songs for mass production” (Cameron and Collins 1997). The popular music industry emerged after the introduction of copyright and the evolution of media. Popular music is regarded as a normal product that can be consumed. However, there is some tension between the commercialized part of the music industry: popular music, and the non-commercialized part of the music industry: art (Tagg 1982). According to an online article, this tension arises because musicians may feel the need to choose between either exploring themselves in music and ‘be artistic’ or composing songs that appeal to the general public and ‘sell themselves out’ (Muller 2014). In the broader context of the creative industries, Hirschman (1983) describes this tension between the commercialized and non-commercialized parts: “commercial success in an aesthetic or ideological setting may be viewed negatively, and those artists and ideologists who achieve commercial success may be denigrated by their peers because they have violated industry norms”.

Further research focuses on music consumption, which is defined as the act of listening to a piece of music (Holbrook and Anand 1990). Much music-related research has been done on consumption instead of purchase, because repeated purchase is not common for music and music can be consumed without purchase (Lacher and Mizerski 1994). Nowadays, through technological developments, it is possible to record music. This *recorded music* is consumed in various places, like cars, at home and at work. At first, before the internet era, pre-recorded music was owned by consumers or played over the radio (Lacher and Mizerski 1994). However, nowadays the ownership of music changes through *streaming*, which: “allows consumers unlimited access to a vast library of content at a fixed monthly payment” (Datta et al. 2018). Thus, consumers less often purchase physical music recordings. Global revenues of physical recordings declined last years to approximately $8 billion and are expected to decrease further to $5 billion by 2022 (PwC 2018). In the meanwhile, the global revenues of live music have increased to $27 billion and are expected to increase above $30 billion by 2022. Moreover, global streaming has increased to $14 billion in the last years and is expected to increase further to approximately $23 billion. Thus streaming becomes more and more important. Furthermore, streaming has led to an increased total music consumption and an increased variety of music (Datta et al. 2018). Despite this large variety of music, a small number of persons dominate the music industry. This is the so-called superstar phenomenon (Chung and Cox 1994; Elberse 2008; Rosen 1981).

Furthermore, Holbrook and Hirschman (1982) state that recorded music is one of the products where the experiential product benefits are of special importance. Experiential benefits are symbolic benefits that are added to products' characteristics, which are experienced by consumers. Scherer and Zentner (2001) describe these experiential benefits as emotional experiences in music. They propose that creators can express emotions in music, which can lead to experienced emotions by consumers through empathy, sympathy and mimicry. Creators add these emotions to recorded music in the production process, when the song is composed. These composers do this through the use of differences in the structure of music, for example with tones, intervals, chores, melodies, rhymes and tempo (Scherer and Zentner 2001). The output of this creative process of composing songs is either a live performance or a recorded song (Cameron and Collins 1997). According to Tschmuck (2012), the value-adding chain of the music industry consists of four central processes. First, (1) Artist & Repertoire (A&R) managers scout new talents for record labels and the newly acquired musicians sign contracts at these labels. Second, (2) these musicians produce music, which is manufactured. The musician composes the music based on the chosen differences in music structure. However, the contracts they have with the record labels may constrain musicians to produce certain types of music. Third, (3) the created music is marketed and promoted, in order to increase sales. Depending on the contract, this marketing is done by (a combination of) the producer, the record labels or an external party like the radio. Fourth, (4) the created recorded music is distributed. Different distribution channels have been used in the past, of which the most recent addition is the internet. In conclusion, all of the four processes work together, and combined they facilitate creativity to emerge (Tschmuck 2012).

Nowadays, BDA is used as well in music composition. For example, newly created songs are tested on fitting a mathematical pattern that is found in popular songs, in order to test its expected success (Witchalls 2004). Moreover, BDA is used, along with machine learning, to create rhythms and rhythm fluctuations and thereby it creates whole new songs (Marr 2017). Another interesting example of the application of BDA in the music industry is the "Adaptive Personalization System", which is proposed by Chung et al. (2009). This system uses massive real time data, which is available in personal music apps nowadays, to automatically download personalized playlists of songs. Although this data is used to predict preferences, it also can be used to inform musicians on how to compose new songs.

Because the use of big data is quite new in the creative industries, not much research on this subject has been done. Most researchers refer to the film and series (content) producing and streaming company Netflix. This company generates 30 million plays and 3 million searches every day (Lycett 2013). Netflix created the idea for their series 'House of Cards', out of their database of customer behavior, because they identified with the help of big data algorithms how the viewers of the original 'House of Cards' series liked certain actors and directors (Erevelles et al. 2016). Moreover, Netflix uses algorithms for recommending their customers on certain films or series (Lycett 2013). These recommending algorithms are used as well in the music industry (Chung et al. 2009).

These examples show that big data can be used in creative industries and can replace or strengthen human creativity in the development of new content. It can strengthen human creativity by testing the music created by humans. Besides, BDA can replace human creativity through the creation of music with algorithms or the decision on certain features of the musical structures based on BDA outcomes on consumer preferences. However, this gives rise to questions like: "if the entertainment producers start giving us exactly what we like, how will we be exposed to new, different and meaningful content that we would never imagine we might be interested in? Art and creativity might not survive in an era where data and algorithms decide what we must read, watch or listen to" (PromptCloud 2017).

4. Theory and Hypotheses

4.1. The Human-Creativity Effect – 'By Whom'

In conclusion from the literature review, both BDA and human creativity are part of idea generation in new content development. However, for new products to be successful, consumers have to buy them. This depends on how consumers perceive the attractiveness of products. Past research shows that this perceived attractiveness can differ for products that are exactly the same, but had a different development process.

One example of such a difference is the paper of Fuchs et al. (2010), which found an empowerment-product demand effect. This effect shows that consumers are more willing to buy a product if they have an influence on the development, than another exactly the same product in objective terms. This influence of consumers in the development process is called co-creation. Another example comes from Hui and Bateson (1991), who find that the pleasantness of service experience is positively influenced by perceived consumer control. A third example, which is more closely related to this paper, is the handmade effect of Fuchs et al. (2015). They find that stated production modes affect the perceived product attractiveness, although the developed product is exactly the same. More specifically, they conclude that handmade products are seen as more attractive than machine-made products that are exactly the same in physical terms, because handmade products contain more love. They propose that these products contain more love, because human creators can produce products with love, which is not possible for machines. Consumers can sense the love of the human creators in products and therefore these products contain more love.

These examples show that products (‘what’) can differ in demand and perceived attractiveness, based on the *process* that is used to develop the product. In this line, this paper looks at human creativity and BDA as different product development strategies (‘by whom’). In chapter 2, I show that both concepts positively influence the product development process, because both lead to an increased generation of ideas and more innovativeness. Although both concepts have this positive influence, the increasing usage of BDA may reduce the influence of human creativity in the development process. Despite the increasing usage of big data, many products are still produced in the ‘old-fashioned’ way: solely by human creativity. Therefore, I propose a *human-creativity effect*: products (‘what’) are perceived as more attractive when they are made by human creativity than when they are created with the help of BDA (‘by whom’). Important for this effect is that human creativity is solely based on human actions and is a heuristic task, where BDA requires machines (e.g. computers) and is done in a more algorithmic way. According to Amabile (1983), heuristic tasks do not have a clear identifiable path to the solution and algorithmic tasks have clear and logical paths. Based on this differences, and several mediators which I will discuss afterwards, I propose:

H_1: Presenting a product as human-creativity made (vs. BDA made) can increase its attractiveness to consumers.

4.2. Mediators of the Human-Creativity Effect – ‘How’

To support the human-creativity effect, I now discuss three factors that I hypothesize are the key drivers of the *human-creativity effect*: *love, creativity* and *privacy concerns*. These drivers explain *how* the human-creativity effect works, through how the different generation strategies (‘by whom’) have a different process (‘how’) that leads to a different perceiving of the attractiveness of the product (‘what’).

Love. BDA needs computers to run tools, where human creativity is solely a human action. Therefore BDA requires machines, where human creativity does not. The end product created with the help of BDA therefore is partly machine-made and the end product created solely with human creativity can be argued to be human-made. Consequently, I expect that the *handmade-effect* of Fuchs et al. (2015) exists in this case as well. They refer to love as *artisanal love*: “in terms of the love that originates with a producer and whose object is the product and its production process”. When products are made with this artisanal love, it is expected that consumers perceive that the end product contains love as well. The idea of artisanal love (love for the production process and for the product itself) originates from literature on organizational behavior. For example, Baum and Locke (2004) find that love for one’s work is a driver for people to participate in the creation of new businesses. Artisanal love is seen as an emotional investment in the product and production process. In this case, BDA is not able to express artisanal love, because BDA is executed with machines. Besides, human creativity is a process that is solely based on humans, who are able to express artisanal love. Therefore, I propose that products that are made with human creativity contain more artisanal love than products that are created with the help of BDA.

Moreover, Fuchs et al. (2015) suggest that products that are made with love (artisanal love), will also be perceived as containing love themselves. Emotions such as love, produced by the creator in the development process of a product can be experienced by consumers. Therefore, I expect consumers to perceive more love in products when these are developed solely by humans than when they are developed, at least partly, through BDA. Furthermore, ‘contains love’ is expected to increase product attractiveness. The ‘contains love’ in products can be associated to positive love feelings a person had during its own life, through a process called evaluative conditioning (Sweldens et al. 2010). These own experiences lead to a more positive evaluation of the product. Because I expect a higher ‘contains love’ for products created by human creativity, I also expect these products to be appreciated more than products created with the help of BDA. In conclusion, I expect love to be a driver in the human-creativity effect.

Creativity. The second difference between BDA and human creativity is the approach: big data follows a more algorithmic approach, where human creativity comes in a more heuristic approach. Heuristic tasks do not have a clear identifiable path to the solution and algorithmic tasks have clear and logical paths. Especially relevant for these two approaches is the notion Amabile (1983) makes: in order to be creative, the task should be heuristic instead of algorithmic, even if the outcome is novel and useful. In the context of NPD, this means that new products are perceived as *creative*, when the development process did not follow a clear identifiable path. Amabile (1983) illustrates this by an example: "an artist who followed the algorithm 'paint pictures of different sorts of children with large sad eyes and use dark-toned backgrounds' would not be producing creative paintings, even if each painting was unique and technically perfect". Based on this, I expect consumers to perceive more creativity from products created by human creativity than from products created with the use of BDA, because consumers perceive the process of human creativity as more heuristic and therefore as more creative.

My next assumption is that products that are more creative are perceived as more attractive. According to Colton and Wiggins (2012), with the consumption of creative products, we also consume the creative process which brought it into being. The product of the creative process should be seen as an invitation for a dialogue between the product, the creator and yourself. Because software is not human, consumers cannot rely on unreasoned ideas about the creative process in people, when reviewing the creative process (Colton and Wiggins 2012). Therefore, positive associations arise when people are able to review the creative process. For products made solely by human creativity, people are fully able to enjoy these positive associations. However, for products created with the help of BDA, software is used, and thereby consumers can rely less on these positive associations. Moreover, in literature on creativity, this concept is defined as a combination of novelty and usefulness. People tend to have novel-seeking behavior (Hirschman 1980) and are expected to find novel products more attractive. Furthermore, products that are perceived more useful are logically expected to have higher product attractiveness. In conclusion, I expect people to perceive products created by human creativity as more creative (i.e. more novel and more useful), than products created with the help of BDA, and therefore these products will have lower attractiveness.

Privacy concerns. According to Kshetri (2014), consumers have growing concerns about data collection methods of organizations. An example of this is shown in the context of direct marketing: for consumers, giving up privacy is a trade-off for shopping-benefits (Phelps et al. 2000). Moreover, they find that more regular purchasers are more privacy concerned. Furthermore, Wedel and Kannan (2016) state that consumers have concerns about how much information companies have about them and that companies ignore laws on privacy. The first concern comes from companies combining datasets and thereby adding consumer information to their data. The second concern arises because laws on privacy have not kept the pace of the increased technology. Thus, privacy issues should not be underestimated.

Two primary drivers in privacy concerns are: (1) the kind of information used and (2) how much influence consumers have on the spreading of this information (Phelps et al. 2000). The more personal the information, the more anxious consumers are. Not using personal information and giving consumers control over how the information is spread, partly solves the issues (Xu et al. 2014). However, many consumers all over the world regard big data as violation of their privacy, because big data does not give them control over what data is used (Manyika et al. 2011). Therefore, privacy concerns grow with the increasing use of BDA. Based on this, I expect consumers to be more privacy concerned for products that are made with the help of big data, than products made solely by human creativity. Because of these growing concerns and negative associations due to privacy issues, I expect that products made with the help of big data are evaluated more negatively than products made solely with human creativity. As a consequence, products that raise more privacy concerns are less attractive. In conclusion, I expect people to be more privacy concerned for products created with BDA, than products created by human creativity, and therefore these products will have lower attractiveness.

In summary, I predict that products created by human creativity will be more attractive to consumers than products created with the help of BDA, because these products are perceived as containing more love, being more creative and arising less privacy concerns. I name the increased attractiveness of human creativity created products: the human-creativity effect. Therefore I hypothesize the following:

H_2: Consumers perceive a product presented as made solely with human-creativity as containing *more love* than a product presented as made with the help of big data analysis [mediation effect of love].

H_3: Consumers perceive a product presented as made solely with human-creativity as *more creative* than a product presented as made with the help of big data analysis [mediation effect of creativity].

H_4: Consumers perceive a product presented as made solely with human-creativity as *causing fewer privacy concerns* than a product presented as made with the help of big data analysis [mediation effect of privacy concerns].

4.3. Conceptual Framework

The main theory and hypotheses above are summarized in the conceptual framework, shown in Figure 2, below.

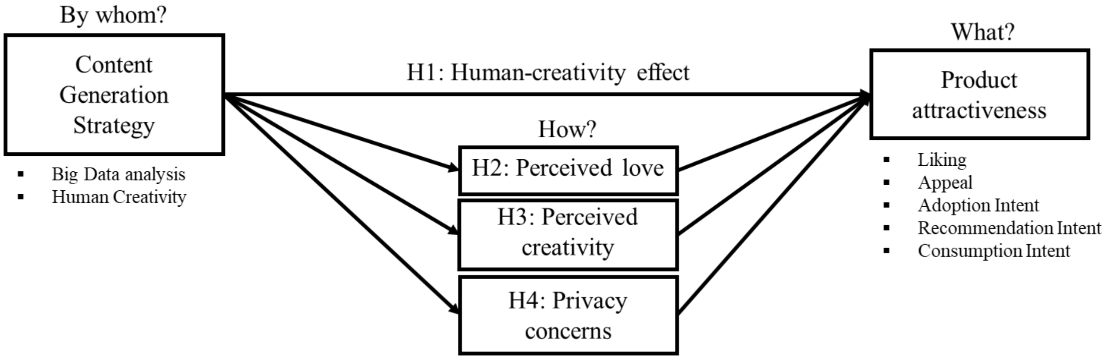

Figure 2 Conceptual Framework

The conceptual framework shows the expected human-creativity effect (H_1) and its expected mediators: perceived (contains) love (H_2), perceived creativity (H_3) and privacy concerns (H_4). These mediators are explaining 'how' the expected human creativity-effect works between the generation strategy ('by whom') and the attractiveness of the end product ('what').

5. Research Methodology

5.1. Participants and Experimental Design

I adopted a between-groups experimental design where I expose all students to the same song but manipulate information pertaining to who and how the song was composed. Specifically, two hundred twenty-nine student-volunteers (N = 229, M_{age} = 22, 56% female) were randomly assigned to one of three possible conditions: the human-creativity condition, the BDA condition or the control condition (I explain these in greater detail below). I chose a between-groups design, because - due to several reasons I now explain - it was not possible for individuals to participate in all conditions. First of all, if respondents would have participated in all scenarios, they would have understood what part of the experiment was manipulated, because they would have seen what changed in the information for different songs. This could have led to socially desirable answers. Second, in order to test each condition on each participant in a within-subjects design, three different songs would be needed, because each song can only meet one of the conditions. In this case, results would be more difficult to interpret, because the preference people have for certain songs would probably be hard to control for. Of course I could randomize the order of songs, and the assignment of songs to treatments but that would complicate the design of my online experiment significantly. In contrast, in a between-group design, only one song is needed and respondents are less likely to figure out the purpose of the experiment. Moreover, people's preference in music has a smaller influence. Although, in the between-group design, people still have different music preferences. However, randomization should mix people's preferences around groups and lead to groups that are not systematically different.

In order to get results that explain the effect targeted in this research, I controlled for music preferences. Besides, in order to avoid that participants try to give social desirable answers, I did not let them know what the other conditions/scenarios were. Moreover, through randomization, I tried to randomly distribute potential influences across groups. Furthermore, in order to manage and obtain the data of the experiment, an online Qualtrics questionnaire has been used, which is described in the following paragraph. Afterwards, I analyzed the gathered data with STATA.

5.2. Procedure

The experiment started with a student clicking on the survey link and thereby becoming a participant. This volunteer was randomly assigned to one of the three following conditions: the *human-creativity condition*, the *BDA condition* or the *control condition*. Each condition included an explanation of how the song was composed, and as extra stimuli a picture to overcome that the between-group design led to weak effects. Moreover, the time spent on this page was measured, so I was able to check for how carefully respondents read the information.

The group of respondents that was assigned to the *human-creativity condition* was told that they were going to listen to a song for a minute, which "*had been composed solely through human creativity*". Besides, the stimuli-picture that was shown was of a female musician, to further prime subjects to think about the human creativity element in music composition. In contrast, participants in the *BDA condition* were given the same information about the song, except for how it was created. They were told that the song "*had been composed with the help of big data analysis on music preferences*" and a stimuli-picture of a data-spreadsheet was shown, to prime subjects to think about the algorithmic nature of music composition with the use of BDA. Finally, in the *control condition* participants were only told that they were going to listen to a song for one minute and no information on how it was composed was given. Moreover, a neutral stimuli-picture (a musical note) was shown.

After these scenarios, all respondents listened for 56 seconds to the exact same song. This part contains the first 56 seconds of: ALMA - Good Vibes featuring Tove Styrke from the album Heavy Rules Mixtape[3]. However, participants were not given this knowledge. The chosen song was published in March 2018, and was not high in charts. Therefore it is likely that it is unknown to respondents. This is important for the credibility of the scenarios. Moreover, the chosen song is regarded pop-music and is quite similar to current popular music across the targeted respondents. In order to check if participants listened to the full part of the song, I measured the time spent on this page.

After listening to the song, participants evaluated the song on attractiveness, perceived contains love, perceived creativity, privacy concerns, perception of the extent to which the song was human-made or machine-made and some control variables (music preferences, listening habits, song recognition and willingness to provide information). The questionnaire ended with an open question asking respondents what they thought the experiment was about. With the answers, I checked if social desirable answers were given by respondents. The full questionnaire is shown in appendix A.

5.3. Power Analysis

Before the data gathering I did research on what sample size is needed for my experimental design, in order to detect significant effects. The sample size is sufficiently large if it has a power (β) of at least 0.8, according to Field and Hole (2002), because "then there is a 80% change of detecting an effect if one genuinely exists." Moreover, I chose to use the standard level of significance (α) of 0.05. Furthermore, I chose to focus on effects of at least a 0.3 correlation coefficient, and therefore at least 85 participants

[3] This song can be found on: https://www.youtube.com/watch?v=nZ7shdhEaHI

are needed according to Cohen (1992). Because I added a control group, I increased the minimum amount of needed participants to 120. The obtained 229 participants are well above this amount.

5.4. Measures

Table 3 gives an overview on the hypothesis and corresponding variables. This table shows, for each hypothesis, which variables are used. After listening to the song, respondents evaluated product attractiveness in line with Fuchs et al. (2015). However, these questions were adjusted to the context of music, because music is less frequently bought. I measured the product's attractiveness on five items using a seven-point Likert scale followed on the question: "How do you evaluate this song?" ("dislike/like", "not appealing/appealing", "unlikely to add to a playlist/likely to add to playlist", "unlikely to recommend to others/likely to recommend to others" & "unlikely to listen again to this song/likely to listen again to this song"; α = .94[4]).

The 'contains love' variable is measured by three items, in line with Fuchs et al. (2015): this song can be described as 'warm', full of 'love' and full of 'passion', all measured by a 7-point Likert scale, where 1 means "strongly disagree" and 7 means "strongly agree" (α = .73). Moreover, I measured the 'made with love' component as well, because this component gives the underlying reason if the perceived 'contains love' in the product originates from the love invested in the composing by the creator. I measured the variable 'made with love', again in line with Fuchs et al. (2015), on a 7-point Likert scale with 1: "strongly disagree" and 7: "strongly agree" on two items: "I think the song is made with passion" and "I think the song is made with love" (α = .80). These questions are asked after the 'contains love' questions, because if these were asked before the 'contains love' questions might got biased by self-generated validity (Fuchs et al. 2015).

Furthermore, creativity is measured. This is a difficult construct and it is often split into other dimensions in order to measure it. These underlying dimensions are: novelty and usefulness (Amabile et al. 1996). I measure the variable 'novelty' on a 7-point Likert scale with 1: "strongly disagree" and 7: "strongly agree" on two items: "I think the song is novel" (Andrews and Smith 1996; Sethi et al. 2001) and "I think the song is original" (Andrews and Smith 1996; Besemer and O'Quin 1986; Besemer 1998). The measurement of the variable 'usefulness' is more difficult to compute,

[4] Cronbach alpha scores are explained in Appendix B.

because people use music in different situations. In these different situations, different types of songs might be useful. Therefore, I introduce the questions that measure usefulness, with the following information: “For answering the next two questions, take in mind the situation when music is most important for you to accomplish a certain task. For example studying, practicing sports or relaxing, etcetera.” After this introduction, the variable ‘usefulness’ is measured on a 7-point Likert scale with: 1 “strongly disagree” and 7: “strongly agree” on two items: “This song is useful in this situation” (Amabile 1983; Besemer 1998; Im and Workman 2004) and “This song is appropriate in this situation” (Amabile 1983; Sethi et al. 2001). The combination of the four Likert scale questions of novelty and usefulness, e.g. creativity, gets a Cronbach alpha score of .73.

Subsequently, privacy concerns were measured on a 7-point Likert scale with 1: “strongly disagree” and 7: “strongly agree” on two newly created items: “I have privacy concerns about how this product was created” and “When listening to the song I was concerned about my privacy”; (α = .56, corr. = .39). The internal consistency and the correlation of this scale are low and therefore, I choose to use the first of these two variables to test my hypotheses, because it is closest to what this research is about. This variable is closest to my research, because it measures the privacy concerns for the process (*how*) and I hypothesize that the use of BDA in the process leads to privacy concerns.

Finally, some questions were asked to add as control variables. Respondents were asked *how old* they were: ‘age’, if they considered themselves as *male*, *female* or *other*: ‘gender’, if they were students *yes* or *no*: ‘student’, on what level of education they were studying (*MBO / HBO / University / Other*) ‘education level’ – based on this variable I created a dummy for ‘university’ –, how much they considered themselves knowledgeable about music (*from not at all knowledgeable* to *very knowledgeable*): ‘music_knowledge’, how often they listened to music (*at least once a day*, *at least once in three days*, *at least once a week*, *less than once a week*; this scale has been turned around afterwards to make this variable better interpretable): ‘listening_habit’, if they were fans of the type of music they listened to in this survey *yes* or *no*: ‘fan_song’, if they recognized the song they listened to *yes* or *no*: ‘recognize_song’ and what their perception was about the proportion that the song was *human-made* versus *machine-made* ‘Human_made check. Furthermore, to control for differences in the willingness to provide information between respondents and groups, I asked them to rate on a 4-point scale how willing they were to provide information on a demographic factor (*age*): 'willingness_age', a lifestyle factor (*two favorite songs*): 'willingness_songs', a purchase-related factor (*how they pay for music*): 'willingness_payments', a personal identifier factor (*mobile phone number*): 'willingness_phone' and a financial factor (*annual income*): 'willingness_income' (α = .67). This is in line with Phelps et al. (2000), who found that people have a different willingness to provide information for these categories. I use this variable to control for the respondents' willingness to give information and to see if this differs between groups. I use a variable, which averages the underlying variables, for this construct and name this 'willingness to provide information'. Furthermore, I asked in an open question, what people thought the experiment was about. No answer fully described the experiment, but most respondents referred to just one part of the experiment. In order to check if respondents did answer according to what they thought the experiment was about, I coded their answers into categories: *I don't know* or *no clue* = 0, something with *big data* = 1, something regarding *privacy* = 2, if they thought it was about *music preferences* = 3 and 4 if they thought it had something to do with *machine-made* music. I explain the distribution across these categories in the next chapter.

Table 3 Summary of Hypotheses

Hypothesis	Content of Hypothesis	Dependent variable(s)	Independent variable(s)
H_1	Presenting a product as human-creativity made (vs. BDA made) can increase its attractiveness to consumers.	Product attractiveness variable.	Content generation strategy variable.
H_2	Consumers perceive a product presented as made solely with human-creativity as containing *more love* than a product presented as made with the help of big data analysis [mediation effect of love].	Product attractiveness variable.	Content generation strategy (production mode) variable, mediator variable: 'contains love' and explaining variable: 'made with love'.
H_3	Consumers perceive a product presented as made solely with human-creativity as *more creative* than a product presented as made with the help of big data analysis [mediation effect of creativity].	Product attractiveness variable.	Content generation strategy (production mode) variable, mediator variable: 'creative'.
H_4	Consumers perceive a product presented as made solely with human-creativity as *causing fewer privacy concerns* than a product presented as made with the help of big data analysis [mediation effect of privacy concerns].	Product attractiveness variable.	Content generation strategy (production mode) variable, mediator variable: 'privacy'.

6. Data Analysis and Results

Pre-treatment. Table 4 summarizes the cleaning of the data for each condition and the full sample. Of the 229 respondents, 33 did not finish the full survey and are therefore dropped. Moreover, one respondent is not a student and does not fit into the target group, so I drop her as well. Finally, 17 respondents did not listen to the full song[5] and their responses are dropped because otherwise this can influence the results. These modifications led to different sizes of condition groups. I also control for if respondents recognized the song. A total of 31 respondents state that they recognized the song. Even though it is highly unlikely that they knew this exact same song (it was really not well-known at the time of the survey, so respondents might have confused the song with other similar songs), I control for song recognition by including the variable '*Recognize_song*' in my regressions, to check if stating that one recognizes the song has a significant effect on outcomes. It has a significant influence in none of the performed linear regressions in this results section, except for the linear model on privacy concerns. Thus, if this variable does measure the extent to which this specific song is recognized, it hardly has an influence. However, I include the variable in the linear regression on privacy, in order to control for possible influences.

Table 4 Pre-treatment

Condition	Control	Human creativity	BDA	Total
Respondents original dataset	76	77	76	229
Not finished the survey	12	9	12	33
No student	-	1	-	1
Not listened to full song	9	4	4	17
Respondents treated dataset	55	63	60	178

Descriptive statistics. The sample characteristics are shown in Table 5. Most of the respondents are female (58.4%), are a university-student (81.4%), are somewhat knowledgeable or knowledgeable about music (80.9%), listen to music at least once a day (86.0%), are not a fan of the type of music that the researched song belongs to (56.7%) and are more willing to provide their age and two favorite songs than their phone number or income. For most of the variables, the randomization works quite well and personal characteristics or preferences are mixed between conditions. However, the human-creativity condition consists of fairly less males than the other two conditions.

[5] Respondents are dropped if they spent less than 57 seconds on the survey-page, i.e., the page where they were instructed to listen to the song.

Table 5 Sample Characteristics

Condition		Control	Human creativity	BDA	Total
Sample Size		55	63	60	178
Gender	Male	45.5%	31.7%	48.3%	41.6%
	Female	54.5%	68.3%	51.7%	58.4%
Age avg.		21.7	22.6	22.7	22.4
Education	MBO	0.0%	1.6%	0.0%	0.6%
	HBO	25.4%	11.1%	16.7%	17.4%
	University	74.6%	85.7%	83.3%	81.4%
	Other	0.0%	1.6%	0.0%	0.6%
Music knowledge	Not at all knowledgeable	12.7%	7.9%	10.0%	10.1%
	Somewhat knowledgeable	43.6%	39.7%	45.0%	42.7%
	Knowledgeable	36.3%	39.7%	38.3%	38.2%
	Very knowledgeable	7.3%	12.7%	6.7%	9.0%
Listening Habit	< once a week	1.8%	1.6%	0.0%	1.1%
	≥ once a week	1.8%	6.4%	3.3%	3.9%
	≥ once in 3 days	7.3%	11.1%	8.3%	9.0%
	≥ once a day	89.1%	81.0%	88.3%	86.0%
Fan of music type		43.6%	44.4%	41.7%	43.3%
Willingness to provide certain information (average of scale 1-4: always willing to never willing)	Age	1.91	1.90	2.07	1.96
	Two favorite songs	1.91	1.97	2.03	1.97
	Method of payments	2.60	2.75	2.45	2.60
	Telephone number	3.58	3.51	3.50	3.53
	Income	3.62	3.60	3.57	3.60
	Average score	2.72	2.75	2.72	2.73
What respondents thought the experiment was about	No clue / did not know	40.0%	41.3%	38.3%	39.9%
	Something with big data	3.6%	6.4%	8.3%	6.2%
	Something with privacy	38.2%	31.8%	21.7%	30.3%
	Music preferences related	16.4%	15.9%	18.3%	16.9%
	Machine-made versus human-made music	1.8%	4.8%	13.3%	6.7%

Moreover, the control condition is composed of relatively more non-university students. Furthermore, respondents in the human-creativity condition see themselves as more knowledgeable about music, but less often listen at least once a day music. Besides, despite no substantial differences in the average willingness to provide information, respondents in the human-creativity condition are less willing to provide information about payments and more willing to provide information about their age than respondents in the BDA condition.

In Table 5, I also show the distribution across categories for what respondents thought the experiment was about. Around 40% of the respondents did not know where the experiment was about. This is evenly distributed across the condition. Moreover, it is quite interesting that there is not much difference between groups in the amount of respondents that thought the experiment was big data related. Despite 'big data' was not named in the survey for the control and human-creativity condition, still many respondents thought this was the goal of the experiment. Furthermore, none of the answers are related to (human) creativity, not even in the human-creativity condition. Moreover, most of the answers are privacy related, even more in the control and human-creativity condition. In the BDA condition, people more often think that the experiment was about machine made versus human-made music. Finally, answers containing music preferences are evenly distributed across conditions.

Preliminary analyses. In order to test the proposed constructs and underlying observed variables, I run a confirmatory factor analyses (CFA) in STATA. Moreover, in appendix C, I show individual CFA models for each constructs, in order to examine extra information about each construct (e.g., fit per construct, etcetera). Figure 3 shows the general CFA model[6]. Table 6 shows the fit indexes of the general model. The model has a high chi-squared. However, the chi-squared depends for some part on the sample size and therefore it is not always seen as accurate (Sawyer and Page 1984). Therefore, I look at other indexes. According to Hu and Bentler (1999), RMSEA should be below .05 to indicate the model as good fit. However, Browne and Cudeck (1993) propose a less strict criteria, with an RMSEA indicating poor fit only when it is higher than .10. Moreover, MacCallum et al. (1996) indicate that RMSEA scores between .08 and .10 are still acceptable, even though with *mediocre fit*, which is the case for my CFA model. According to Hu and Bentler (1999), CFI and TLI scores ideally exceed .90, which is not the case for my CFA model. However, my fit is comparable to the fit of the CFA model of Patterson et al. (2005) and, following this prior research, I conclude that the CFI and TLI scores are acceptable. Furthermore, Hu and Bentler (1999) suggest a cutoff rate for SRMR close to .08, which is the case for the CFA model. Thus, although the test statistics are not optimal, the overall pattern of results in Table 6 allows me to conclude that my CFA has sufficiently acceptable fit.

This CFA model shows six constructs: *product attractiveness*, *contains love*, *made with love*, *creativity*, *privacy concerns* and *willingness to give information*. I discuss each in turn. First of all, all items for product attractiveness have a significantly high positive effect on the construct. Furthermore, the AVE score of .77 (Table 7)

[6] This figure shows only the significant covariance between constructs, *p <.05, **p < .01, ***p < .001. Moreover, it contains the standardized coefficients. The first item for each construct is the marker, because the unstandardized coefficients of these items are constrained to 1.

indicates that much of the variance of the items is explained by this construct, and is clearly above the reliability threshold often adopted by researchers which is .50 (Fornell and Larcker 1981). This supports the psychometric properties of the *product attractiveness* scale. Hence, in subsequent analyses, I constructed construct scores for product attractiveness by averaging the corresponding items that compose each score.

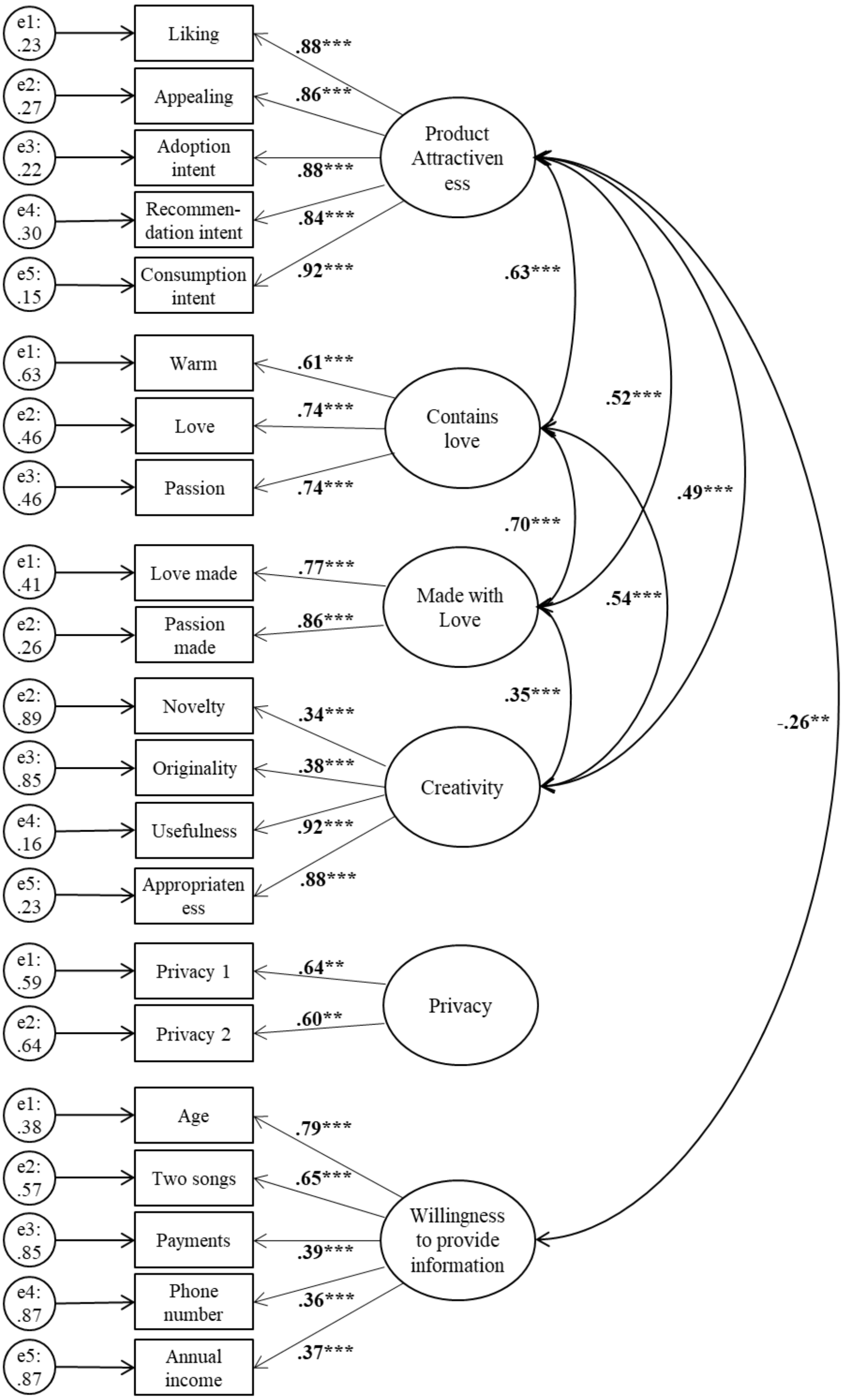

Figure 3 CFA Model with Standardized Coefficients

Table 6 CFA Fit Indexes

Fit indexes	Whole CFA model
χ2 (df)	414.040*** (174)
RMSEA	.088
CFI	.866
TLI (NFI)	.839
SRMR	.084

Table 7 Average Variance Extracted of Constructs

Construct	AVE
Product attractiveness	.768
Contains Love	.489
Made with Love	.666
Creativity	.470
Privacy concerns	.385
Willingness to provide information	.293

In a similar vein, all items for the construct '*contains love*' have a significantly positive effect on the construct. The AVE score of .49 (Table 7) is just below the threshold of .50 for reliability (Fornell and Larcker 1981). Hence, I constructed construct scores for 'contains love' by averaging the corresponding items, because the reliability is basically acceptable and it is much more insightful to keep this construct in the model than leaving it out due to reliability concerns. Moreover, I look at the construct '*made with love*'. Both items for 'made with love' have a significantly positive effect on the construct. The AVE score of .67 (Table 7) is adequate. Hence, I constructed construct scores for 'made with love' by averaging the corresponding items.

Next, I look at the construct creativity. All items for *creativity* have a significantly positive effect on the construct. This construct is largely explained by a combination of usefulness and appropriateness. However, the AVE score of .47 (Table 7) is slightly below the reliability threshold of .50. Hence, I constructed construct scores for creativity by averaging the corresponding items.

Finally, the AVE of the construct *privacy concerns* is below acceptable (AVE = .39, Table 7), therefore I decide to use the first underlying item in further analysis, as already suggested in the method section. The last construct '*willingness to provide information*' is a construct that I use to control for social desirable answers and I measure on different items. The construct does not explain the variance of the underlying items well (AVE = .29, Table 7). However, all the underlying items are different types of information and therefore I still decide to use the average of these types of information to construct the scale of 'willingness to provide information'.

Manipulation check. To check whether my manipulations worked, I measure to what extent respondents perceive the product as human-made or machine-made. I measure this by asking on a 1 to 7 scale "*What is the proportion you regard this song as human-made or machine-made*". A three-way ANOVA on this variable 'Human-made check' produces no significant effect ($F(2,175) = .41$, ns[7], Table D[8].3). This indicates that no significant differences exist in the extent to which the song is perceived human-made or machine-made. However, most of the variance is explained within groups. In order to control for the heterogeneity within groups, I perform a three-way ANCOVA analysis (Table D.5), controlling for some demographical information, music preferences, music knowledge and listening habits. Although the variance explained is higher than for the ANOVA, the ANCOVA does not explain much variance as well ($R^2 = .047$, Table D.5). I observe no significant effects of the conditions in the ANCOVA analysis ($p > .05$, Table D.5). Furthermore, a linear regression model results in no significant different effects of the conditions on the dependent variable ($p > .05$, Table D.7). Besides, I perform a Kruskal-Wallis test as a robustness check, in which I again find no significant difference between the individual conditions ($H(2) = .508$, ns, Table D.6). Thus, in my sample, there is no evidence that telling respondents that a product is made by either human creativity, the help of BDA or no production cue, does lead to a difference in the extent to which a product is perceived to be human-made or machine-made. This also means that a direct test does not provide evidence for the existence of the human-made effect in my data. However, the proposed human-creativity effect is only partly hypothesized on the human-made effect. Therefore, I continue with testing the human-creativity effect, despite not finding direct evidence for one of its proposed drivers: the human-made effect.

[7] Not significant
[8] Appendix D

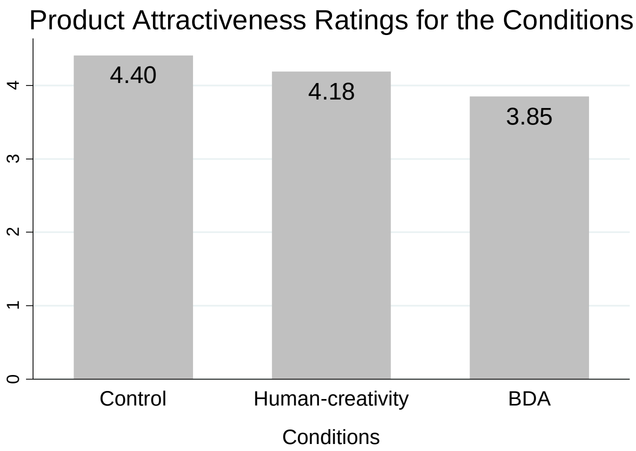

Figure 4 Product Attractiveness Sample Means per Condition

Product attractiveness. I first test whether, between all conditions, product attractiveness ratings differ. Figure 4 shows the sample means of the ratings for 'product attractiveness'. In order to see if these means are significantly different from each other, I conduct an ANCOVA[9], in which I control for demographical information, willingness to provide information, music preferences, music knowledge, and listening habits[10]. The ANCOVA reveals a significant difference between the BDA condition and the control condition for the product attractiveness rating (F (1,176) = 12.0, p < .01, Table E[11].5). However, I find no such significant difference between the human-creativity condition and the control condition (ns, Table E.5). In order to see what the effect size differences are between conditions, I perform a linear regression with the same control variables. This linear regressions shows that, ceteris paribus, respondents in the BDA condition rate the product's attractiveness significantly lower than respondents in the control condition (β = -.66, p < .01, Table E.6). Thus, respondents in the BDA condition, ceteris paribus, rate the product's attractiveness on average almost 10 percent lower than respondents in the control condition. This means that telling respondents that a product is made with the help of BDA results in a significant lower rating on the product's attractiveness. Furthermore, telling consumers that a product is created solely with human creativity, does not lead to significant higher product attractiveness than in the control condition, when no cue on the production process is told. A possible reason for this is: producing products solely with human creativity is still the default and therefore this leads to no differences to a condition where no

[9] Due to high heterogeneity within groups, the same analysis with ANOVAs instead of ANCOVAs does not reveal significant differences. Therefore, I do not include the ANOVAs in the main analysis.
[10] In further analyses below, I name these variables 'the control variables'.
[11] Appendix E.

information is given on the production process. Thus, respondents in the control condition basically assume that the product is made with human creativity, just as respondents in the human-creativity treatment is told. In conclusion, respondents in the BDA condition rate the product's attractiveness significantly lower than respondents in the control and human-creativity condition, between which I do not find such difference. This confirms hypothesis 1, because conditions in which respondents thought the song is created with human creativity are perceived as more attractive, than products of which respondents think that these are made with the help of BDA.

The linear regression results in the following model:

$$Product\ Attractiveness\ rating = -.66 * Big\ data\ condition + .11 * Age + .46 * Female + 1.53 * Fan\ of\ music\ type - .45 * Willingness\ to\ provide\ information + e$$

Some control variables are of particular interest. Specifically, I find a significant positive effect of age ($\beta = .11$, $p < .01$, Table E.6) and being female on the product's attractiveness rating ($\beta = .46$, $p < .05$, Table E.6). Furthermore, as one would expect, the largest significant effect on the product's attractiveness rating is due to respondents that like the type of music to which the song belongs to ($\beta = 1.53$, $p < .001$, Table E.6).

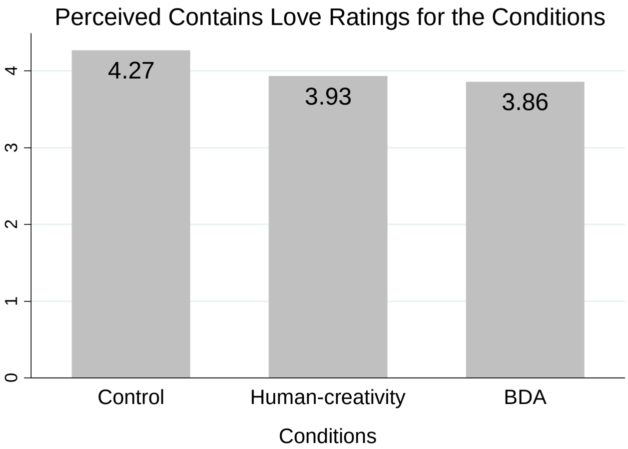

Figure 5 Contains Love Sample Means per Condition

Love. Figure 5 shows the sample means of the ratings for 'contains love'. Of particular interest is that the sample means of perceived 'contains love' are very similar between both treatments, and the control condition has a much higher mean. In order to see if these means are significantly different from each other, I perform a linear regression[12] on the condition variable and the '*contains love'* variable, including the control variables. This linear regressions shows, ceteris paribus that respondents in the

[12] Because the ANCOVA outcomes are quite similar to the regression outcomes, I report the ANCOVAs in Appendix E from now on, to confirm the regression outcomes.

BDA condition rate the 'contains love' significantly lower, than respondents in the control condition (β = -.50, p < .05, Table E.10). This means that telling respondents that a product is made with the help of BDA results in a significant lower 'contains love' in the product. Furthermore, respondents in the human-creativity condition rate the 'contains love' significantly lower, than respondents in the control condition (β = -.44, p < .05, Table E.10). This means that telling respondents that a product is made solely with human creativity, results in a significant lower 'contains love' in the product. Thus, both treatments in which information was given on the production process, are rated significantly lower on the 'contains love' in that product. This does not support hypothesis 2, where I propose that products created with the help of human creativity lead to a higher perceived love containing in the product, than for products made with the help of BDA. The linear regression results in the following model:

$$\begin{aligned} &\textit{The extent to which the product is perceived to contain love} \\ &\quad = 2.30 - .44 * \textit{Human creativity condition} - .50 * \textit{Big data condition} - .10 \\ &\quad * \textit{Age} + .89 * \textit{Fan of music type} + e \end{aligned}$$

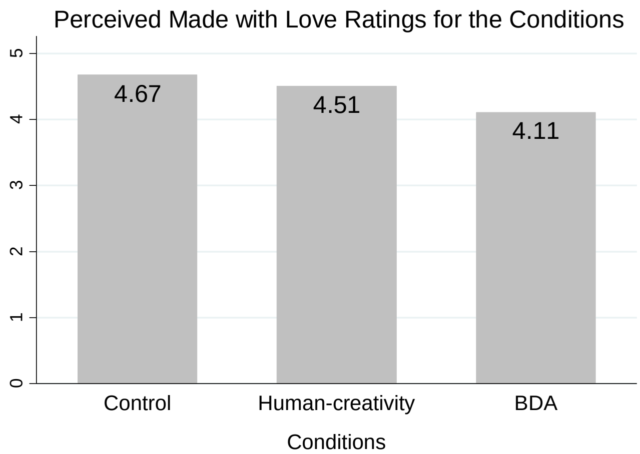

Figure 6 Made with Love Sample Means per Condition

Furthermore, the sample means of the ratings for 'made with love' are shown in Figure 6. I perform a linear regression[13] on the condition variable and the '*made with love'* variable, including the control variables, in order to see if the reported means are significantly different. This linear regressions shows, ceteris paribus, that respondents in the BDA condition on average rate 'made with love' significantly lower, than respondents in the control condition (β = -.54, p < .05, Table E.15). This means that respondents who are told that a product is made with the help of BDA perceive

[13] For 'Made with Love', ANOVA finds significant differences. However, these outcomes are the same as the outcomes of the regression and with regression it is easier to interpret the size of this effect. The ANOVA outcomes are in Appendix E.

significantly lower that the corresponding product is made with love. Furthermore, the regression shows, ceteris paribus, that respondents in the human-creativity condition do not significantly differ in the ‘made with love’ rating, than respondents in the control condition (ns, Table E.15). This means that telling respondents that a product is made solely with human creativity, results in the same expectation of that the product is made with love than when no information on the production process is given. In summary, while respondents in the BDA condition report a significant lower perceiving of the product to be made with love, in comparison to giving no information on the production process, the respondents who are told that the product is made solely with human creativity do not significantly differ to the control condition. This supports hypothesis 2, because I expect that products made solely with human creativity, are perceived as more made with love, than products made with the help of BDA. However, I also expect that this higher perceived made with love, results in a higher perceived ‘contains love’. The regressions on both constructs only show such indication for the control condition, because although the human-creativity condition has a higher ‘made with love’ rating than the BDA condition, this is not the case for the ‘contains love’ rating. The linear regression on ‘made with love’ results in the following model:

$$\begin{aligned} &\textit{The extent to which the product is perceived to be made with love} \\ &\qquad = 4.05 - .54 * \textit{Big data condition} + .72 * \textit{Fan of music type} + e \end{aligned}$$

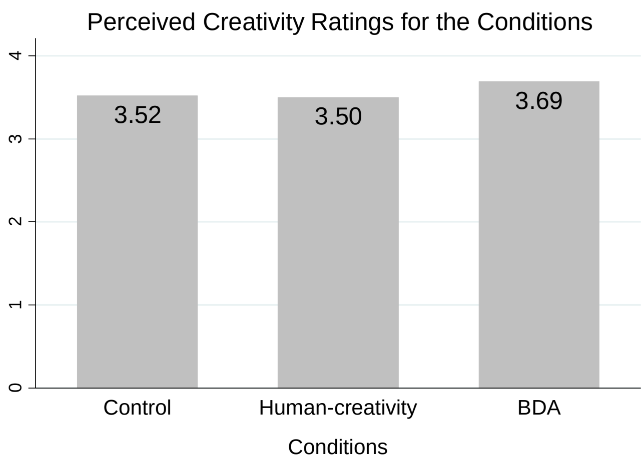

Figure 7 Creativity Sample Means per Condition

Creativity. Figure 7 shows the sample means of the ratings for perceived ‘creativity’. I conduct a linear regression on the creativity and the condition variable, including control variables, to see if there are significant differences between these means. This regression shows, ceteris paribus, no significant statistical difference between the treatments (human-creativity & BDA) and the control condition (ns, Table E.20). This means that both telling respondents that a product is made with the help of BDA and telling them that a product is made solely with human creativity, do not result in a significantly different perceiving of the product's level of creativity than if no information on the production process is given. This is in contradiction to hypothesis 3, in which I expect that products created solely with human creativity are perceived as more creative, than products created with the help of BDA. The results from the regression do not support such an effect. The linear regression on creativity results in the following model:

$$\begin{aligned} &Perceived\ creativity\ in\ the\ product \\ &\qquad = 2.77 - .26 * Music\ knowledge + 1.29 * Fan\ of\ music\ type + e \end{aligned}$$

Of particular interest is the significant positive effect of the respondent's music knowledge ($\beta = -.26$, $p < .05$, Table E.20), which indicates, ceteris paribus, that people who see themselves as more knowledgeable about music, indicate the song as less creative. Furthermore, the regressions shows, ceteris paribus, that the largest significant effect on the creativity rating, as one expects, is due to respondents that like the type of music to which the song belongs to ($\beta = 1.29$, $p < .001$, Table E.6).

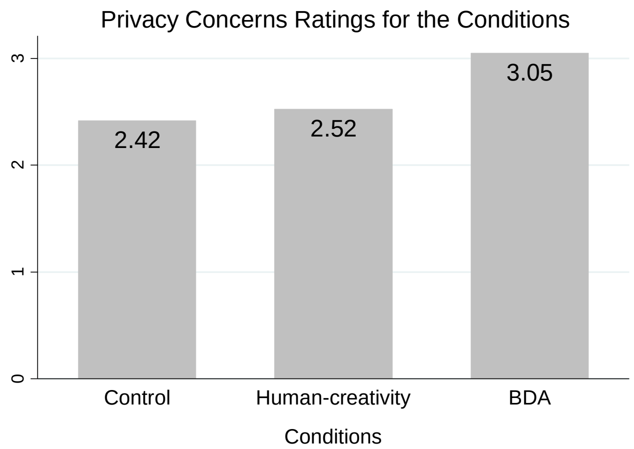

Figure 8 Privacy Concerns Sample Means per Condition

Privacy concerns. Figure 8 shows the sample means of the ratings for 'privacy concerns'. In order to see if these means are significantly different from each other, I run a linear regression on privacy concerns and the condition variable, including the control variables. This linear regressions shows, ceteris paribus, that respondents in the BDA condition rate their privacy concerns significantly higher, than respondents in the control condition ($\beta = .65$, $p < .05$, Table E.25). This means that telling respondents that a product is made with the help of BDA results in significant higher privacy concerns than when respondents receive no information on how the product is produced. The linear regression does not show, ceteris paribus, a significant difference between the control and human-creativity condition (ns, Table E.25). In summary, telling consumers that a product is created with solely human creativity, does not lead to significant different privacy concerns than telling consumer nothing about the production process. However, telling respondents that a product is created with the help of BDA does lead to more privacy concerns. This supports hypothesis 3, where I expect higher privacy concerns to arise for products that are created with the help of BDA than products created with human creativity. The linear regression on privacy concerns results in the following model:

$$Privacy\ concerns = .60 * Big\ data\ condition + .65\ Respondents\ who\ recognized\ the\ song + e$$

Of particular interest is the effect of respondents who indicate that they recognized the song. These respondents perceive significantly more privacy concerns, than respondents who did not recognize the song ($\beta = .65$, $p < .05$, Table E.25). Furthermore, respondent’s willingness to provide information has no significant effect on their privacy concerns ($p > .05$, Table E.25). Thus, I do not detect an effect of how willing respondents are to give certain types of information, on how privacy concerned they are, which one could have expected, as privacy concerns and willingness to give information are closely related. Even if the willingness to give information is split up, none of the underlying willingness for types of information has a significant influence on the privacy concerns of respondents (ns, Table E.25).

Multiple mediation. I perform two multiple mediations, including the proposed mediators love, creativity and privacy concerns, on the effect of the human-creativity and BDA conditions on the perceived product attractiveness. The multiple mediations are done in line with Preacher and Hayes (2008). The structural building of the model and further explanation are included in appendix F. As expected, I find a significant direct effect of the BDA condition dummy on product attractiveness ($\beta = -.46$, $p < .01$, Table F.1), which indicates that products created with the help of BDA analysis have a lower perceived product attractiveness. I find no such a significant effect for the human-creativity condition dummy. However, as stated earlier, the reason that I do not find significant differences could be that human-creativity produced products are still the default. Because half of the data that is not in the human-creativity condition, is in the control condition, where respondents also think that products are made with human-creativity. These results show that products created with the help of BDA are perceived as less attractive than products created solely with human creativity, which confirms (H1) the human-creativity effect. The human-creativity effect consists of a negative effect of the use of BDA in the production process, instead of the default (human creativity), on the product attractiveness.

The results of a bootstrapping test show that the effect of the BDA condition dummy on the product attractiveness is mediated by privacy concerns ([CI_{BCa}[14]$_{, 95\%}$]: .01, .19, Table F.2). This effect consists partly of a significant highly positive effect of the BDA condition dummy on privacy concerns ($\beta = .54$, $p < .05$, Table F.1). Because the overall effect is positive, one should expect a positive effect of privacy concerns on product attractiveness as well. However, this is not common sense and I doubt this because of the following two reasons. First, I do not find a significant effect of privacy concerns on product attractiveness in the seemingly unrelated regression (ns, Table F.1). Second, because the mediation effect is just above zero, and the effect of the BDA condition dummy on product attractiveness is significantly large, the effect of privacy concerns on product attractiveness has to be very low and therefore might not be significantly different from zero. Thus, I find that the use of BDA in the production process, instead of human creativity, leads to more privacy concerns. However, this does not lead to a lower perceived product attractiveness. This only partly supports hypothesis 4. Furthermore, I do not find significant mediation effects of ‘contains love’ and creativity. Hence, with this analysis, I do not find support for hypothesis 2. However, this analysis may be incomplete or may be incorrectly specifying the *mechanism* through which production mode (i.e., content generation strategy) influences product attractiveness perceptions. Consequently, below I conduct a second analysis on ‘contains love’ through a sequential mediation analysis, which confirms that the mechanism through which BDA influences perceived attractiveness is through a sequential effect on (1) *made with love* perceptions, on a first stage, and only then (2) *contains love* perceptions. I discuss this sequential mediation below. Besides, I do not find support for hypothesis 3, which I reject, because I find no evidence for a mediation effect of creativity.

Sequential mediation. In line with Fuchs et al. (2015), I run a sequential mediation on the proposed mediator *love* (both ‘made with love’ and ‘contains love’ perceptions). The structural model of this sequential mediation is shown in Figure F.3

[14] 95% bias corrected and accelerated confidence interval

(basically, the sequential process assumes that *production mode* – i.e., content generation strategy – influences *made with love* perceptions, which in turn influence *contains love* perceptions which, ultimately, drive *product attractiveness*). The results of the bootstrapping show, in line with Fuchs et al. (2015) that there is a significant sequential indirect effect from the production mode to 'made with love' to 'contains love' to product attractiveness for the BDA condition (β = -.08, [$CI_{Perc., 95\%}$]: -.17, -.01; [$CI_{BC., 95\%}$]: -.18, -.02, Table F.4). This sequential mediation shows that products created with the help of BDA lead to a lower perceived 'Made with love' (β = -.46, $p < .05$, Table F.3), which in turn leads to a lower perceived 'Contains love' (β = .45, $p < .001$, Table F.3), which in turns lead to a lower perceived product attractiveness (β = .37, $p < .001$, Table F.3). This is in line with the theory of Fuchs et al. (2015), who argue that the 'contains love' in products is due to the artisanal love of a producer. In this case, products created with the help of BDA are perceived as less 'made with love' than products created with human creativity (both the human-creativity and control condition). In turn, 'made with love' causes "contains love", which has an effect on product attractiveness.

Moreover, the sequential mediation shows that the hand-made effect might be present in the human-creativity effect. If this is not the case, then a similar effect does appear, because both the human-creativity treatment and the control condition have higher perceived product attractiveness, through the sequential mediation of 'made with love' and 'contains love'. Thus, I confirm hypothesis 2, which indicates a mediation of the human-creativity effect through 'contains love'. Of particular interest is that the direct effect in this model is not significant, which indicates that the whole effect in this model is explained by the sequential mediation. Therefore, the "handmade effect", and love-related perceptions, seem the key driver in the human-creativity effect. However, in this case the demonstration of the handmade effect is done via its absence in the BDA condition. In other words, because human-created products are the default, the BDA condition has a lower product attractiveness through the absence of the handmade effect and therefore products created with the help of BDA are perceived as less attractive.

All in all, I find evidence for the human-creativity effect, but slightly different than proposed. The human-creativity effect is a higher perceived attractiveness for products created solely with human creativity than products created with the help of BDA. I show that this occurs due to the presence of the handmade effect. However, because human creativity is actually the default production mode, I find that the human-creativity effect is due to the absence of the handmade effect in the BDA condition. In short, producing content, and new products in general, with the help of BDA may hurt a product's or content's attractiveness, because such products/content are perceived as designed "without love".

7. Conclusion

7.1. General Discussion and Academic Contribution

In this section I discuss the obtained results. First of all, I find the existence of a human-creativity effect: the tendency of consumers of creative products, such as movies, songs or video games, to perceive a product as more attractive when it is created solely with human creativity than when it is created with the help of BDA. In the first place, I expect that this effect would lead to a higher perceived product attractiveness for products created solely with human creativity, than for both products created with the help of BDA and products for which no information on how it is produced has been given. However, I find no difference in product attractiveness for respondents in the human-creativity condition and control condition. This is in contradiction to the findings of Fuchs et al. (2015) for their handmade effect, in which they found that respondents in the handmade condition perceived the product as more attractive than respondents in the control condition. However, in my case, I suggest that this difference is due to that for the product I used (i.e. a song) the default production still is solely human creativity and that for the product Fuchs et al. (2015) used (i.e. a scarf) the default production mode is machine-made. Thus, it seems plausible that respondents indeed considered human creativity as the default production mode. All in all, I confirm Hypothesis 1 and the human-creativity effect: products created solely with human creativity are perceived as more attractive than products created with the help of BDA. Because I argue that human creativity is the default production mode, this effect causes a lower perceived product attractiveness for products created with the help of BDA, because human creativity is (partly) absent in this production mode.

Furthermore, I proposed several possible mediators for the human-creativity effect: 'contains love', creativity and privacy concerns. I find evidence that 'contains love' is a driver in the human-creativity effect in a sequential way. First of all, the producer is perceived to make his/her products with love for the production process. Thereafter, consumers perceive this love that is put into the product and perceive that the product contains love itself. Finally, this love in the product leads to a higher perceived attractiveness of the corresponding product. I find, through the sequential mediation, that products created with the help of BDA are perceived as less ‘made with love’, which leads to lower ‘contains love’ and in turn to lower product attractiveness, than products created with human creativity. This confirms Fuchs et al.'s (2015) theory on how products are made with love and therefore contain love. Moreover, the presence of this effect shows that the handmade is present in the human-creativity effect as well. However, this effect is present in an opposite direction: the absence of the handmade effect in BDA created products leads to a lower perceived product attractiveness. Thus, products that are made solely with human creativity are perceived as more handmade, than products made with the help of BDA, and therefore have higher product attractiveness. In conclusion, I confirm hypothesis 2 and find a mediation effect of ‘contains love’ on the human-creativity effect.

Moreover, I find no evidence of a mediating role of perceived creativity on the human-creativity effect. Besides, I do not find a difference in perceived creativity (e.g. perceived novelty and perceived usefulness) for products that are created with the help of BDA and products that are created solely by human creativity. Furthermore, I do not find a mediation effect of creativity. Therefore, I reject hypothesis 3 and propose that products created with the help of BDA and products created solely with human creativity are perceived as evenly creative.

Furthermore, I find that products created with the help of BDA cause significantly more privacy concerns, than products created with human creativity. However, these privacy concerns do not explain the human-creativity effect, because higher privacy concerns do not lead to a lower product attractiveness. An overall positive mediation effect even suggests that higher privacy concerns lead to a higher product attractiveness, however I find that if this effect exists it is very small and likely to not deviate significantly from zero. In conclusion, I reject hypothesis 4 and find no mediation effect of privacy concerns on the human-creativity effect, although I find differences for privacy concerns between the production modes.

In summary, I contribute to current literature on the influence of the production mode on how a product is perceived, through introducing the human-creativity effect: products that are created solely with human creativity are perceived as more attractive than products created with the help of BDA, although these products are exactly in the same physical state. I also test competing theoretical mechanisms to explain this effect and show that it is mainly driven by “love-related” perceptions about the product. In other words, this effect is mainly mediated through the hand-made effect (i.e. through artisanal love that is put into the product). Moreover, I find that the perceived creativity is not different between the production modes, but that BDA created products lead to higher privacy concerns. However, the latter does not lead to a different perceived product attractiveness.

7.2. Managerial Implications

Beside the theoretical significance of my findings, these have plain practical and managerial implications as well. First of all, musicians should compose their songs with human creativity instead of BDA, because then their songs are perceived as more attractive. However, this only holds when consumers do know about the production process, because human creativity still is the default. Consumers expect songs to be made with human creativity. Thus, if the use of BDA leads to better songs, but A&R managers, producers, record labels and musicians do not want the human-creativity effect to occur – which leads to a lower perceived attractiveness of their song –, they should not give information to the consumers about how the song is composed. Then, consumers will regard this music as created with human creativity, because this is the default.

Second, I do not expect that market songs as human creativity does lead to higher song attractiveness, because consumers already expect this as the default. Only when BDA becomes the default production mode, market songs as made with human creativity might result in higher perceived song attractiveness. Third, composing songs with the help of BDA leads to higher privacy concerns. Although I find no effect of these concerns on the attractiveness of songs, A&R managers, producers, record labels and musicians should be aware of the privacy concerns. Although they do not have an effect on the song's attractiveness, they might affect other product characteristics as WTP. Fourth, musicians do not have to be afraid that their songs are seen as less creative when they are made with the help of BDA.

Because the music industry has a lot in common with the other creative industries, these findings might hold in these industries as well. In my introduction, I used Netflix's production of 'House of Cards' as an example. House of Cards might have been less attractive to consumers, if they knew that it was produced with the help of BDA before they started watching the series. If this is the case, it might even be that the series did not become as successful as it has. Therefore, if my results are applicable to creative industries, companies like Netflix should be careful with the use of BDA or do not let consumers know that they used BDA. Furthermore, they should take into account that producing with the help of BDA can lead to higher privacy concerns. Although this does not affect the attractiveness of content, it might harm other factors. For example, in order to use Netflix, you need an online account, where you fill in personal data and payment methods. Consumers might get restrained to activate such accounts, if they are privacy concerned. Moreover, companies like Netflix do not have to be concerned about the perceived creativity of their content, if these are made with the help of BDA.

Finally, my results might be applicable to the broader context of new product development, because the development of content is a substantial part of NPD. Because marketing managers, in general, need to serve customers in the best way possible, they need to take the human-creativity effect into account. If their products are created with the help of BDA, then these products might be perceived as less attractive in terms of liking and consumption intent. Thus, although BDA offers lots of benefits and has a positive influence on the development of new products, it has drawbacks as well. It could even be that these drawbacks are more significant than the benefits and then managers should use solely human creativity instead of BDA in the production process. An important implication for managers is that consumers still see human creativity as the default option in the creation of new products. Therefore, the drawbacks of BDA are not present if consumers do not know how the product is produced. Hence, marketing managers should not promote their products as made with big data.

7.3. Limitations and Directions for Future Research

This research is the first approach on the human-creativity effect, for as far as I know, and therefore it consists of several limitations. Moreover, there are many opportunities for further research.

First, it is likely that differences in the human-creativity effect occur across different products and respondent groups. I use a piece of popular music as product in my research to find and indicate the human-creativity effect. Because this is a very specific product, this could harm the external validity of the effect. Therefore, I suggest that further research looks into other classes of products, outside the music industry or even creative industries, in order to confirm the human-creativity effect for other products as well. Furthermore, I do research on a group of students in The Netherlands, which is only an approximation of general consumers. Therefore, further research should look into other geographical and demographical groups. Even better would be consumer panels.

Second, I perform the experiment trough an online survey. This method has a primer benefit: respondents are in a situation where they normally consume a product (i.e. listen to a song). However, through such an experiment, it is not possible to control for all external factors. For example, although I controlled for their listening time, I cannot control for how carefully respondents listened. Moreover, I do not know how carefully they thought about the questions and to what extent they processed the information given on how the product was produced. Therefore, it would be interesting to replicate this study in an experimental laboratory setting.

Third, I proposed the third hypothesis, the mediation of creativity, based on the statement of Colton and Wiggins (2012), who indicate that because software is not human, consumers cannot rely on unreasoned ideas about the creative process in people, when reviewing the creative process. I find no difference in perceived creativity for the different production modes. However, Colton and Wiggins (2012) also state that: “Computational systems are not human, and so the creativity they exhibit will be creativity, but not as we know it: never exactly the same as in humans.” Future research should look into this difference in creativity and what role it plays in the human-creativity effect.

Finally, in my research I find that the human-creativity effect exists for the production mode on the perceived attractiveness of products. I based the product’s attractiveness on liking, appeal, consumption intent, recommendation intent and adoption intent. However, Fuchs et al.'s (2015) findings show that effects like the human-creativity effect can hold for constructs like willingness to pay (WTP) as well. Therefore, I suggest that further research should be done on generalization of the human-creativity effect to WTP. For this research, I advise to not make use of a consumption product like music, but a more-often purchased product.

8. Appendices

8.1. Appendix A: Online Questionnaire

Start of Block: Page 1

Hello.

Thank you in advance for participating in this experiment and helping me in my graduation trajectory at the MSc Economics & Business (Major: Marketing) at the Erasmus School of Economics.
In this experiment you will listen to a song and evaluate it. So please fill in the survey in a place where you can listen to music, using headphones is okay. This questionnaire will take you around 5-10 minutes to finish.

Kind regards,
Gertjan

Please go to the next page.

End of Block: Page 1

Start of Block: Page 2

Random one of three scenarios:

BDA condition: You are going to listen to a one-minute part of a song. This song has been composed with the help of *big data analysis*, meaning that decisions on musical factors and characteristics have been decided based on algorithms ran on a big data set containing information about human music preferences. Examples of these characteristics are: speed of the music, the variation in the music, the length of tones, etcetera. Please go to the next page.

Music_pref

No. ID	Msc_speed	Msc_vari	Tone_lngth	Msc_gap	Msc_Style	Msc_
1	3	7	3	4	7	
2	4	7	4	2	7	
3	2	6	2	3	6	
4	6	7	6	4	7	
5	4	7	4	3	5	
6	7	6	3	4	4	
7	3	7	4	2	3	
8	7	7	2	3	4	
9	7	6	3	4	2	
10	6	7	4	2	7	

Human-creativity condition: You are going to listen to a one-minute part of a song. This song is made solely by *human creativity*, meaning that the artist has used its own creativity to create this song and to decide on the song's characteristics. Examples of these characteristics are: speed of the music, the variation in the music, the length of tones, etcetera. Please go to the next page.

Control condition: You are going to listen to a one-minute part of a song. Please go to the next page.

Time_info: Timing (not shown to participants)
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

End of Block: Page 2

Start of Block: Page 3

Please listen to the song-part below by clicking on play and listen in for the full 56 seconds.

If you are ready, click on this button:

O I listened to the full song. (1)

Time_song Timing (not shown to participants)
First Click (1)
Last Click (2)
Page Submit (3)
Click Count (4)

End of Block: Page 3

Start of Block: Page 4

How do you evaluate this song? Rate on a scale from 1 to 7 for the following factors:

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 (7)	
Dislike	o	o	o	o	o	o	o	Like
Not appealing	o	o	o	o	o	o	o	Appealing
Unlikely to add to a playlist	o	o	o	o	o	o	o	Likely to add to a playlist
Unlikely to recommend to others	o	o	o	o	o	o	o	Likely to recommend to others
Unlikely to listen again to this song	o	o	o	o	o	o	o	Likely to listen again to this song

End of Block: Page 4

Start of Block: Page 5

What do you think of this song? Please indicate to what extent you agree or disagree with the following statements:

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
The song can be described as warm (warm)	O	O	O	O	O	O	O
The song can be described as full of love (love)	O	O	O	O	O	O	O
The song can be described as full of passion (passion)	O	O	O	O	O	O	O
I think the song is made with love (love-made)	O	O	O	O	O	O	O
I think the song is made with passion (passion-made)	O	O	O	O	O	O	O

Please indicate to what extent you agree or disagree with the following statements:

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I think the song is novel (novel)	O	O	O	O	O	O	O
I think the song is original (original)	O	O	O	O	O	O	O

Please indicate to what extent you agree or disagree with the following statements:

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I have privacy concerns about how this product was created (privacy1)	O	O	O	O	O	O	O
When listening to the song I was concerned about my privacy (privacy2)	O	O	O	O	O	O	O

End of Block: Page 5

Start of Block: Page 6

For answering the next two questions, take in mind the situation when music is most important for you to accomplish a certain task. For example studying, practicing sports or relaxing, etcetera.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
The song is useful in this situation (Useful)	O	O	O	O	O	O	O
This song is appropriate in this situation (Appropriate)	O	O	O	O	O	O	O

End of Block: Page 6

Start of Block: Page 7

Just a few personal questions left, on this last page, which I need to control for in the experiment.

How old are you?

Slide the bar to your current age:

0 10 20 30 40 50 60 70 80 90 100

What is your gender?

- O Male (1)
- O Female (2)

Are you a student?

- O Yes (1)
- O No (2)

On what education level are you studying?

- O MBO (1)
- O HBO (2)
- O University (3)
- O Other (4)

How much consider you yourself knowledgeable about music?

- O Not at all knowledgeable (1)
- O Somewhat knowledgeable (2)
- O Knowledgeable (3)
- O Very knowledgeable (4)

How often do you listen to music?

- O At least once a day (1)
- O At least once in three days (2)
- O At least once a week (3)
- O Less that once a week (4)

Are you a fan of the type of music you listened to in this experiment?

- O Yes (1)
- O No (2)

Did you recognize the song you listened to in this survey?

O Yes (1)

O No (2)

What is the proportion you regard this song as human-made or machine-made?

	1 (1)	2 (2)	3 (3)	4 (4)	5 (5)	6 (6)	7 (7)	
Human-made	O	O	O	O	O	O	O	Machine-made

Indicate your willingness to provide information to a music producing company in the following situations:

	Always willing (1)	Somewhat willing (2)	Not very willing (3)	Never willing (4)
How willing are you to provide your age? (Willingness_age)	O	O	O	O
How willing are you to provide your two favorite songs? (Willingness_songs)	O	O	O	O
How willing are you to provide the way you pay for music? (Willingness_payments)	O	O	O	O
How willing are you to provide your telephone number? (Willingness_phone)	O	O	O	O
How willing are you to provide your annual income? (Willingness_income)	O	O	O	O

What do you think the experiment was about? You may fill in 'Don't know'.

Open question: ____

End of Block: Page 7

End of Survey: Page 8

You have reached the end of the experiment. Thank you for your time!

If you are wondering what the experiment was about or if you have any further questions, feel free to contact me by e-mail: 471906gb@eur.nl .

Thanks again for participating and helping me in my graduation trajectory at the MSc Economics & Business (Major: Marketing) at the Erasmus School of Economics.

Kind regards,
Gertjan Bos

8.2. Appendix B: Cronbach's α (alpha) Scores

The Cronbach’s α score for the product attractiveness scale is .94 as shown in Table B.1. This score indicates that the scale has a high internal consistency and a variable that sums up the underlying Likert scales can be created. Furthermore, Table B.1 shows that all variables are correlating well, because for every variable the stated alpha score is lower than the scale’s alpha score. This means that dropping one of the variables in the scale, will decrease the overall alpha score.

Table B.1 Cronbach’s α Product Attractiveness

Item	Item-test Correlation	Item-rest correlation	Average inter-item correlation	Alpha score
Liking	.9107	.8576	.7588	.9264
Appeal	.8904	.8266	.7740	.9320
Adoption intent	.9051	.8491	.7629	.9279
Recommendation intent	.8719	.7987	.7879	.9370
Consumption intent	.9290	.8860	.7450	.9212
Test scale			.7657	.9423

The Cronbach’s α score for the ‘contains love’ scale is .73 as shown in Table B.2. This is not a very convincing score, but still is seen as reliable, because it is higher than a .70 alpha score. Thus, a variable that sums up the underlying Likert scales can be created. Clearly, love is the most important variable in this scale, because the alpha score will decrease a lot if this variable is dropped out of this scale. Dropping one of the other variables will lower the alpha score as well.

Table B.2 Cronbach’s α Perceived Contains Love

Item	Item-test Correlation	Item-rest correlation	Average inter-item correlation	Alpha score
Warm	.7740	.4952	.5561	.7148
Love	.8604	.6597	.3470	.5152
Passion	.7862	.5169	.5266	.6899
Test scale			.4766	.7320

The Cronbach’s α score for the perceived made with love scale is .80 as shown in Table B.3. This table looks a bit different than the ones before, because it only contains two variables. This is a trustworthy score, because it is higher than a .70 alpha score. Thus, a variable that sums up the underlying Likert scales can be created.

Table B.3 Cronbach's α Perceived Made with Love

Variables in scale	Love_made and Passion_made
Number of items in the scale:	2
Average inter-item correlation for scale:	.6610
Scale reliability coefficient (Alpha score):	.7959

The Cronbach's α score for the perceived creativity scale is .73 as shown in Table B.4. This is not a very convincing score, but still is seen as reliable, because it is higher than a .7 alpha score. Thus, a variable that sums up the underlying Likert scales can be created. The alpha score can be increased slightly, if novel is dropped out of the scale (.7343 > .7315). However, in this case I stick to current literature and keep this variable to explain the construct creativity, because the overall alpha score is sufficient.

Table B.4 Cronbach's α Perceived Creativity

Item	Item-test Correlation	Item-rest correlation	Average inter-item correlation	Alpha score
Novel	.9107	.4094	.4794	.7343
Original	.8904	.4542	.4490	.7097
Useful	.9051	.6266	.3411	.6083
Appropriate	.8719	.6097	.3511	.6188
Test scale			.4051	.7315

The Cronbach's α score for the perceived privacy concerns scale is .56 as shown in Table B.5. This score indicates that the internal consistency of this scale and corresponding variables is not sufficient. However, Iacobucci and Duhachek (2003) state that Cronbach's α scores are generally low for scales based on two variables, because the α score is partly based on the number of variables. Hence, sometimes the correlation coefficient is used. In this case, the correlation coefficient between both variables is .386, which is fairly low. Therefore, I choose to use the fist variable to test my hypotheses, because this variable describes the proposed construct better.

Table B.5 Cronbach's α Perceived Privacy Concerns

Variables in scale	Privacy_1 and Privacy_2
Number of items in the scale:	2
Average inter-item correlation for scale:	.3858
Scale reliability coefficient (Alpha score):	.5568

The Cronbach's α score for the willingness to give information scale is .67 as shown in Table B.6. Although most often a minimal alpha score of .70 is seen as reliable, sometimes scores above .60 are used. These scores are seen as neither reliable nor unreliable. Dropping one of the underlying variables is no option, because this will decrease the overall alpha score of the scale even further. Therefore, I choose to create a variable summing up the underlying variables of this scale, because it is better than leaving out this construct.

Table B.6 Cronbach's α Willingness to Give Information

Item	Item-test Correlation	Item-rest correlation	Average inter-item correlation	Alpha score
Willingness to give age	.7062	.4937	.2634	.5885
Willingness to give two favorite songs	.6204	.3739	.3104	.6429
Willingness to give payment method	.6365	.3957	.3016	.6333
Willingness to give phone number	.6515	.4162	.2934	.6241
Willingness to give income	.6722	.4450	.2820	.6111
Test scale			.2901	.6714

8.3. Appendix C: CFA for Each Individual Construct

In order to check if the proposed constructs, which were measured with Likert scaled questions, were valid, I perform several confirmatory factor analyses (CFA). I show the overall CFA model in the main results. However, I perform an individual CFA for each construct as well. For each construct, I extract a standard model where each underlying variable is treated the same in explaining the construct. Moreover, if other possible underlying paths make sense, I check if a model including these paths leads to better fit indexes, to get better insights. I use the following significance levels in this appendix: *p <.05, **p < .01, ***p < .001. Moreover, I show the standardized coefficients.

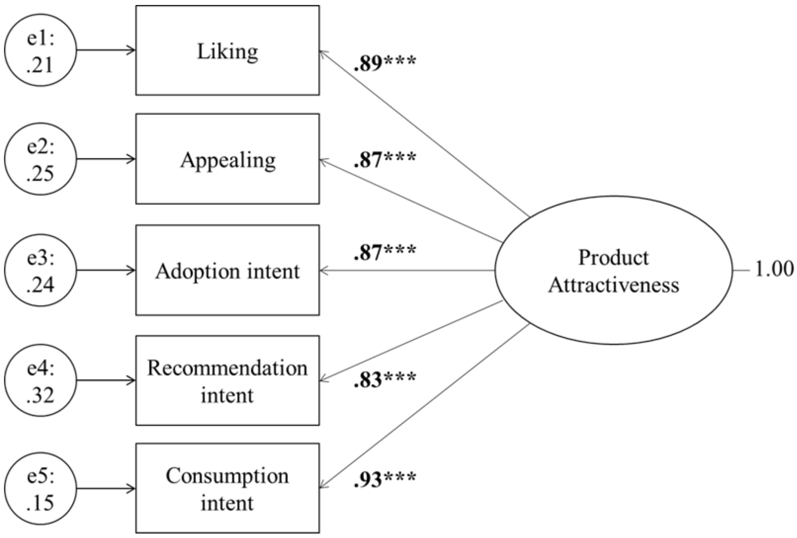

Figure C.1 Standard CFA Model Product Attractiveness

Product attractiveness. For this construct, I show the standard CFA model outcome in Figure C.1. This figure shows that all indicator loadings have a highly significant and highly positive influence on product attractiveness. The fit indexes of this model are shown in Table C.1. This table shows that the standard model has a high chi-squared. But, in order to have a good fit, the p-value for the chi-squared should exceed .05, which is not the case. However, the chi-squared depends for some part on the sample size and therefore it is not always seen as accurate (Sawyer and Page 1984). Hence, other indexes are used to measure the model fit. One of these indexes is the root mean square error of approximation (RMSEA), which is above 0.1 and therefore this model does not fit well according to Browne and Cudeck (1993). The comparative fit index (CFI) is just above .9, which is adequate. Furthermore, the Tucker-Lewis index (TLI), also known as the normed fit index (NFI) is below .95, which indicates again that the fit of the model is not optimal. Moreover, the standardized root mean square residual (SRMR) requires a score below .08 for a good fitting model (Hu and Bentler 1999), which is the case. Moreover, the average variance explained (AVE) is .77, which is quite high and exceeds the needed score of .50 for the explanation of the variables' variances in the model. All in all, several obtained indexes indicate that the model can perform better.

Table C.1 CFA Product Attractiveness

	Product attractiveness	
Fit indexes	**Standard model**	**Modified model**
χ2 (df)	85.827*** (5)	5.948(3)
RMSEA	.301	.074
CFI	.908	.997
TLI (NFI)	.815	.989
SRMR	.040	.008
AVE	.767	.741

Therefore, I propose a modified model. This model fits well according to all indexes stated in Table C.1. Despite that all observable variables have a significant and large effect on the latent variable in the standard model, the modified model fits the sample data better. The standard model is modified with two added covariance factors: one between the error terms of 'liking' and 'appealing' and the other between the error terms of 'adoption intent' and recommendation intent'. These observable variables are, within the context of explaining the latent variable, more related to each other and co-vary to a certain extent. For example, liking and appealing are two closely related constructs, because these can be used intertwined. The modified model is shown in Figure C.2.

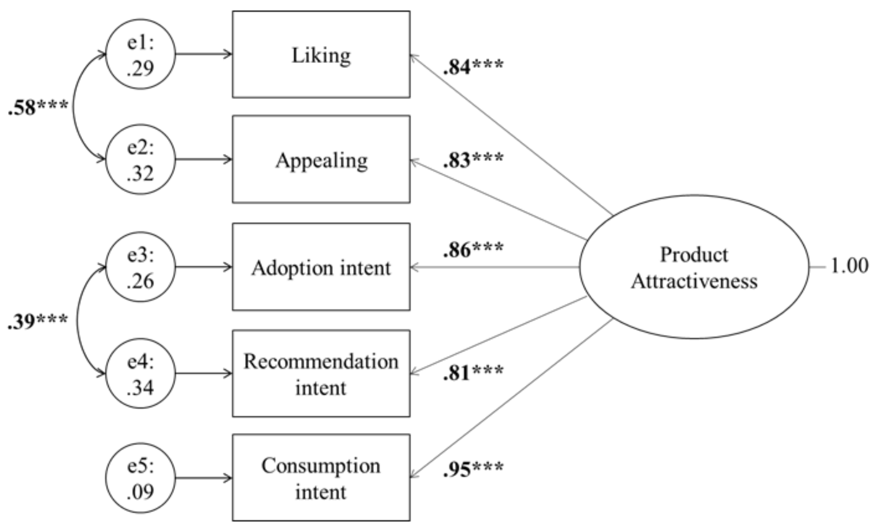

Figure C.2 Modified CFA Model Product Attractiveness

The individual CFA on the construct product attractiveness shows that the underlying observable variables explain the construct well and none of these should be left out. Therefore, as the Cronbach alpha score in appendix B already indicated, a variable for product attractiveness that averages the observable variables can be created.

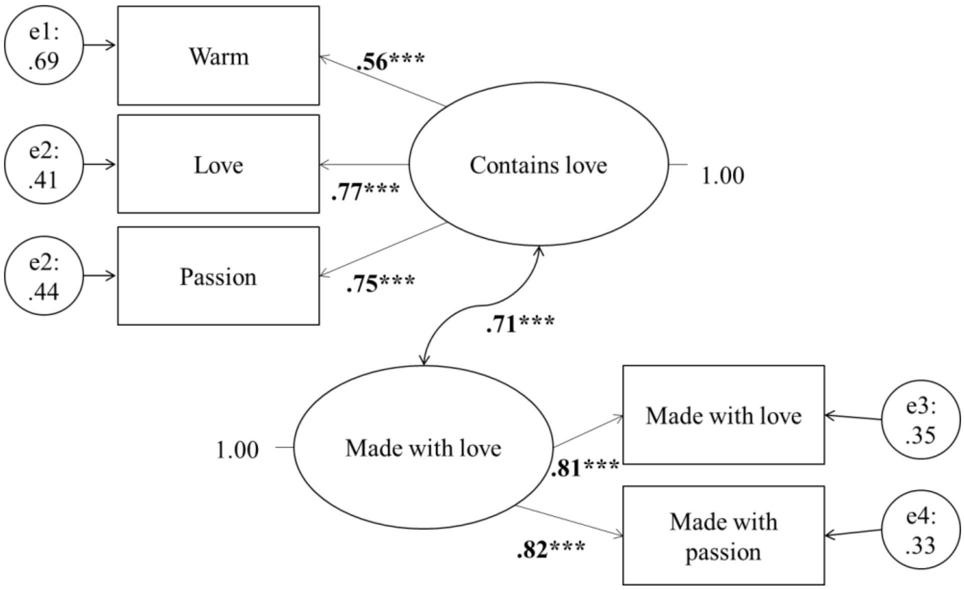

Figure C.3 Two-latent CFA Model Contains Love and Made with Love

Contains love and Made with love. For the construct 'contains love', the degree of freedom in the obtained standard model is zero and therefore it is not possible to affirm or reject the model. This is due to the low amount of observed variables for this construct. Moreover, for the construct' made with love', CFA is not possible, because CFA requires more than two underlying variables. Therefore I run a two-latent CFA on both together. A two-latent CFA runs a model on two latent variables, while controlling for covariance between both variables. The obtained model is shown in Figure C.3.

The model shows that all observed variables have highly positive and significant effects on the constructs. However, the observed variables 'love' and 'passion' have a higher influence on the contains love construct, than the observed variable 'warm'. Furthermore, the model shows that the two latent variables have a high and significant covariance, which indicates that these constructs are closely related. Moreover, this indicates that products perceived as containing love, are perceived to be created with love as well, which supports the underlying reasoning for the 'handmade-effect'.

Table C.2 CFA Contains Love & Made with Love

	Contains love & Love-made
Fit indexes	**Two-latent model**
χ2 (df)	32.245 (4)
RMSEA	.199
CFI	.907
TLI (NFI)	.768
SRMR	.050
AVE	.556

Table C.2 shows the fit indexes of the proposed two-latent model. The outcomes are mixed: the model scores well on CFI, SRMR, but performs poorly according to the chi-squared, RMSEA and TLI. However, the AVE is adequate. Therefore, I use the variables averaging the observable variables for both constructs, because the Cronbach's alpha scores in Appendix B are adequate as well.

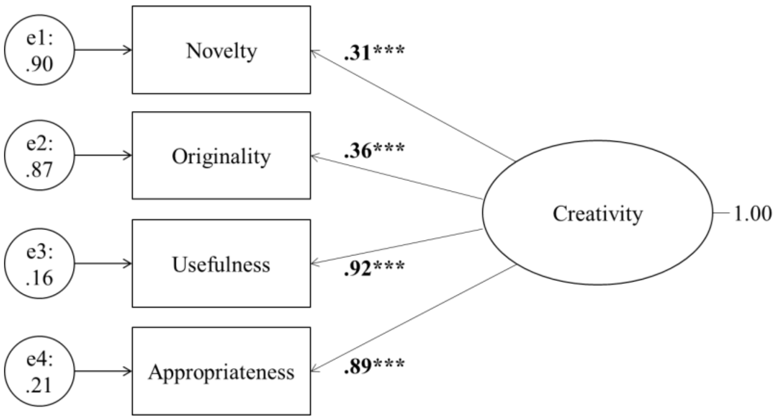

Figure C.4 Standard CFA Model Creativity

Creativity. A standard CFA model for the construct creativity is shown in Figure C.4. This model does not perform well, according to Table C.3. All scores indicate that the model does not fit the construct well. Moreover, the AVE is quite low. The reason for this is the low variance explained for the observed variables of the novelty part, which is shown by their high error terms in Figure C.4. In the standard model, the construct creativity is largely explained by the observed variables that explain the usefulness part. Therefore, I expect the underlying observed variables for both novelty and usefulness to covariate. Based on this, I propose modified model 1, where covariates are added to the CFA model, between novelty and originality, and between usefulness and appropriateness. However, the obtained model has zero degrees of freedom and cannot be interpreted. Because of this, I create the modified models 2 (the standard model with a covariance between novelty and originality) and 3 (the standard model with a covariance between usefulness and appropriateness). Table C.3 shows that both models fit the data well, indicated by all indexes. However, the AVE decreases even more and therefore these models are not useful as well.

Table C.3 CFA Creativity

Fit indexes	Perceived creativity				
	Standard model	**Modified model 1**	**Modified model 2**	**Modified model 3**	**Modified model 4**
χ2 (df)	30.799 (2)	.308 (0)	.308 (1)	.308 (1)	.308 (1)
RMSEA	.284	.000	.000	.000	.000
CFI	.887	1.000	1.000	1.000	1.000
TLI (NFI)	.662	1.000	1.016	1.016	1.016
SRMR	.094	.004	.004	.004	.004
AVE	.463	No significance	.459	.323	.641

In order to find a more fitting model, I run a two-latent CFA on the constructs novelty and usefulness, which I expect to explain the creativity construct. The obtained model is shown in Figure C.5. This model fits the data well and explains a fair amount of the variance in the variables, according to Table C.3. Moreover, Figure C.5 shows that the observed variables have a positive and highly significant influence on both latent variables. Although, for the construct novelty, the error terms are somewhat higher. This model clearly indicates that novelty and usefulness are two different constructs, but also significantly covariate with each other. Because the model uses standardized variables as input, the covariate can be interpreted as the correlation coefficient. Therefore, novelty and usefulness have a positive moderate linear relationship, according to this model.

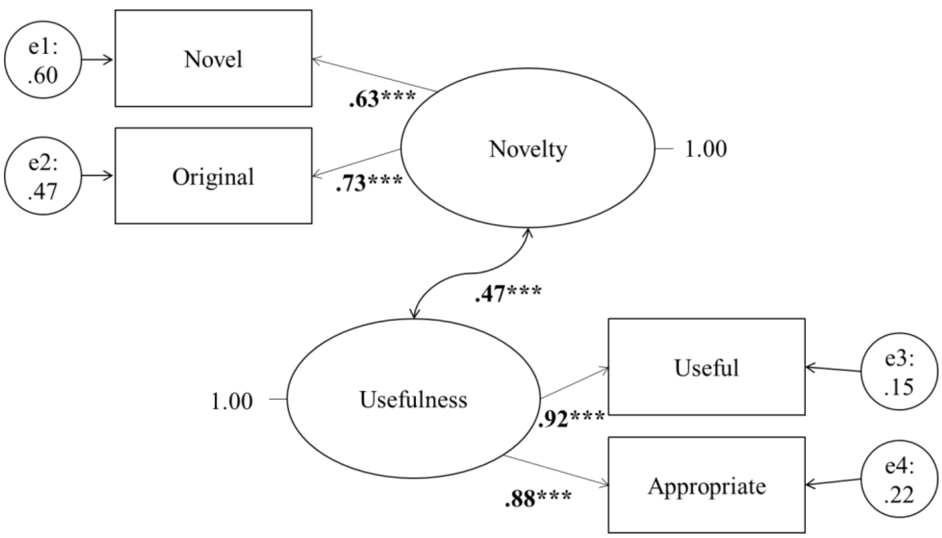

Figure C.5 Two-latent CFA Model Creativity (Novelty and Usefulness)

All in all, the two-latent CFA model indicates that the construct of creativity consists of the positively related constructs novelty and usefulness, which are in turn explained by the observed variables. This shows, in combination with the alpha score (app. B), that it is possible to measure creativity by averaging the underlying scales. However, as Figure C.4 shows, the construct usefulness may have a bigger influence on creativity. Based on this information and the obtained Cronbach's α, I decide to use a variable that is averaging the underlying four variables.

Privacy. Because this construct is measured by two variables, individual CFA is not possible.

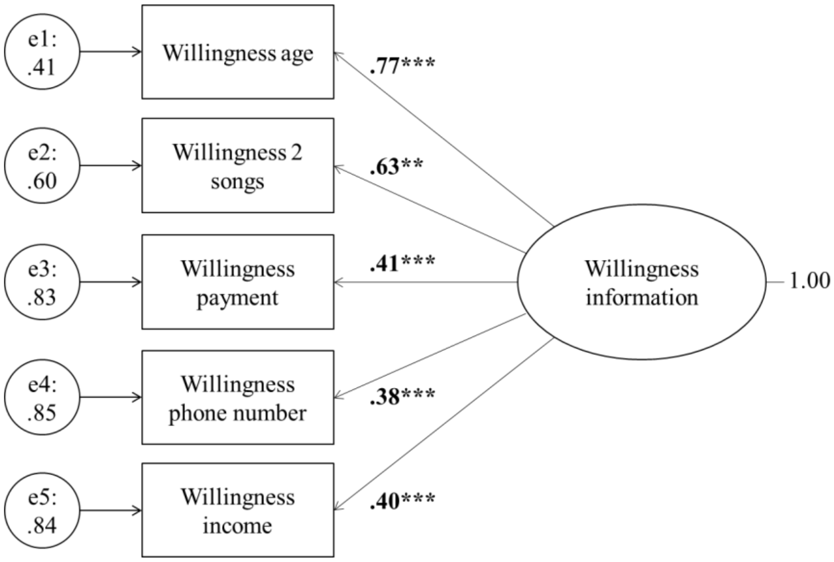

Figure C.6 Standard CFA Model Willingness to Give Information

Willingness to give information. Figure C.6 shows a standard CFA model for willingness to give information. All observed variables have a significant positive effect on the construct. However, the largest effect comes from the willingness to provide one's age. The other variables still have high error terms, which indicate that these are not explained well by the model and in the latent. Table C.4 shows this as well, by the low AVE score. Moreover, according to this table, all the fit indexes indicate that this model does not fit well. Therefore, I moderate the model and include the covariance of the error terms between willingness to provide one's age and to provide one's two favorite songs and the error terms between willingness to provide one's phone number and one's income. This moderated CFA model is shown in Figure C.7.

Table C.4 CFA Willingness to Give Information

	Information willingness	
Fit indexes	**Standard model**	**Modified model**
χ2 (df)	54.122 (5)	2.227 (3)
RMSEA	.235	.000
CFI	.684	1.000
TLI (NFI)	.367	1.017
SRMR	.101	.017
AVE	.294	.237

The moderated CFA model again shows the positive significant effects of the observed variable on the latent. According to Table C.4, this model does fit the data well. However the AVE is still low. This is also shown by the large error terms in Figure C.7. This means that it is difficult to fit the underlying observed variables into one latent. So, in this sample, the relationship between the different types of data and how willing respondents are to provide this data, is not clear linear. Therefore, I choose to use the variable averaging the observed variables, because the alpha score in Appendix B was adequate. Despite that the underlying variables not exactly measuring the same construct, the averaging variable is still useful, because it averages the willingness to provide different types of information. Thus, despite people are not that linear in willingness to provide different types of information, the created variable explains their average willingness over these types of information.

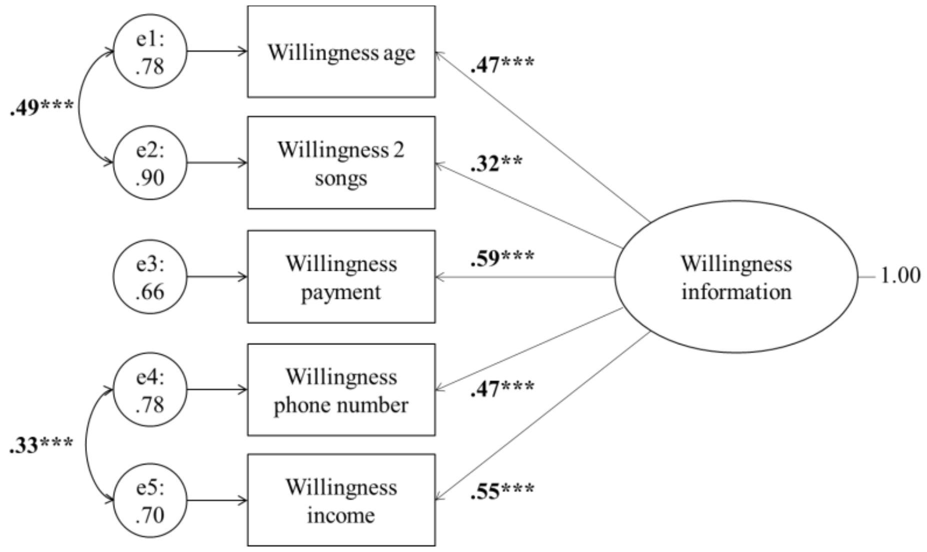

Figure C.7 Moderated CFA Model Willingness to Give Information

8.4. Appendix D: Manipulation Check

Manipulation check. In this appendix, I provide the analysis for the manipulation check. The variable 'Human-made check' is used to control for the success of the manipulation. This variable is constructed on a 1-7 scale by "*What is the proportion you regard this song as human-made or machine-made*". First of all, I do a Shapiro-Wilk W Test for normality and a Levene's Test for homogeneity of variances on this variable, because normality of data for each treatment or control condition and homogeneity of the variances of these conditions are two of the assumptions underlying analysis of variance (ANOVA). Table D.1 shows that only the BDA condition consists of significantly normal distributed data ($D(60) = .97$, $p > .05$). The control condition ($D(55) = .90$, $p < .001$) and the human-creativity condition ($D(63) = .95$, $p < .05$) significantly deviate from normality. However, the homogeneity of variances assumption is not violated, according to the Levene's Test in Table D.2 ($F(2, 175) = 1.48$, $p > 0.05$).

Table D.1 Shapiro-Wilk W Test for Normal Data on Human-made Check

Condition	Obs.	W	V	Z	Prob>z
Control	55	.90121	5.010	3.456	.00027
Human-creativity	63	.94863	2.904	2.304	.01060
BDA	60	.96916	1.676	1.114	.13274

Table D.2 Levene's Test for Homogeneity of Variances on Human-made Check

	Levene statistic	df1	df2	Sig.
Levene's test using the mean	1.481	2	175	.230
Levene's test using the median	.988	2	175	.374
Levene's test using the 10% trimmed mean	1.927	2	175	.149

I run a 3x1 one-way independent ANOVA on human-made check and the condition variable. Afterwards, I run a Tukey post hoc test to compare differences between conditions. Because the normal Tukey post hoc test requires equal sample sizes, I use the Tukey-Kramer adjustment. The results of the ANOVA, in table D.3, show different means for the groups. These means are around 4.7, which indicates that on average the song is perceived as more machine-made than human-made. Moreover, I find no significant differences between groups ($F(2, 175) = .41$, $p > .05$). Furthermore, a Tukey post hoc test in table D.4 reveals no significant differences between specific groups ($p > .05$). The ANOVA test in table D.3 shows that most of the variance is explained within groups. This indicates that there is too much heterogeneity within each condition.

Table D.3 ANOVA on Human-made Check

	Sum of Squares	df	Mean square	F.	Sig.
Between Groups	1.587	2	.794	.41	.6614
Within Groups	335.160	175	1.915		
Total	336.747	177	1.903		
Condition	**Mean**	**SD**			
Control	4.67	1.32			
Human-creativity	4.79	1.35			
BDA	4.57	1.48			
Total	4.68	1.38			

Table D.4 Tukey Post Hoc Multi Comparison Test on Human-made Check

Condition				95 % CI	
First condition	**Second condition**	**Mean difference (A-B)**	**Sig.**	**Lower Bound**	**Upper Bound**
Control	Human-creativity	.121	0.884	-.483	.724
Control	BDA	-.106	0.911	-.717	.505
Human-creativity	BDA	-.227	0.635	-.817	.363

Because of the substantial amount of heterogeneity within groups, I perform an ANCOVA analysis where I control for gender, age, education, music knowledge, music preference and listening habits. Moreover, in order to see if significant effects exist of these independent variables on the dependent variable, I run a linear regression with the same control variables. Both are shown in Table D.5. The ANCOVA model shows that the residual still is substantial and the model explains little of the variance of the experiment control variable. This is also indicated by the low R-squared for both models. Moreover, both treatments do not significantly declare some of the variance of the experiment control variable. However, the control variable Fan song – if respondents were a fan of the type of music they listened to in the experiment – does significantly declare somewhat of the variance ($F(1,176) = 10.1$, $p < .05$). The linear regression shows that being fan of this type of music has a significantly negative effect on the experiment control variable ($\beta = -.49$, $p < .05$). This indicates that respondents, who indicate that they are a fan, perceive the song more human-made than non-fan respondents.

Because the assumptions for parametric tests are somewhat violated, I run the non-parametric Kruskal-Wallis Test, as a robustness check to see if the results from the ANCOVA analysis hold. The outcome of this test, in Table D.6, shows that there was no significant difference between conditions in if the product is perceived more human-made or machine-made ($H(2) = .508$, $p > .05$).

Table D.5 ANCOVA and Linear Regression Model on Human-made Check

Variables	**ANCOVA model (partial SS)**	**Linear regression model (coefficient and SE)**	
Human-creativity condition dummy	.131	.069	(.264)
BDA condition dummy	.381	-.112	(.264)
Age	1.397	.040	(.047)
Gender	1.483	.192	(.218)
University	3.189	-.355	(.274)
Music knowledge	.783	.093	(.146)
Listening habit	.867	-.140	(.208)
Fan song	10.110*	-.490*	(.212)
Residual	321.093		
Model	15.654		
Constant		4.495***	(1.293)
R-Squared	.047	.047	
F	1.03	1.03	
N	178	178	

Standard errors in parentheses for regression, control condition used as base-level
* p<0.05, ** p<0.01, *** p<0.001

Table D.6 Kruskal-Wallis Equality-of-Populations Rank Test on Human-made Check

Condition	**Obs.**	**Rank Sum**	**Mean Rank**
Control	55	4930	89.63
Human-creativity	63	5830.5	106.01
BDA	60	5170.5	86.18
Test Statistics	Chi-squared	df.	Prob.
With ties in data	.508	2	.78

8.5. Appendix E: Mean and Effect Size differences

In this appendix, I provide the statistical tests that are used for testing if any differences exist in means and effect size for several constructs.

Product attractiveness. The created scale-variable 'product attractiveness' is used to test for differences in how the product was perceived, between the treatments and control condition. Table E.1 shows that the BDA condition ($D(60) = .97$, $p > .05$) and human-creativity condition ($D(63) = .99$, $p > .05$) consist of significantly normal distributed data. However, the control condition ($D(55) = .95$, $p < .05$) significantly deviates from normality. The homogeneity of variances assumption is not violated, according to the Levene's Test in Table E.2 ($F(2, 175) = 1.21$, $p > 0.05$).

Table E.1 Shapiro-Wilk W Test for Normal Data on Product Attractiveness

Condition	Obs.	W	V	z	Prob>z
Control	55	.94559	2.759	2.177	.01476
Human-creativity	63	.98510	.842	-.371	.64458
BDA	60	.96553	1.874	1.354	.08794

Table E.2 Levene's Test for Homogeneity of Variances on Product Attractiveness

	Levene statistic	df1	df2	Sig.
Levene's test using the mean	1.210	2	175	.301
Levene's test using the median	1.072	2	175	.346
Levene's test using the 10% trimmed mean	1.182	2	175	.309

Because the assumptions for parametric tests are not highly violated, I run a 3x1 one-way independent ANOVA on product attractiveness and the condition variable. Afterwards, I run a Tukey post hoc test to compare differences between conditions. Because the normal Tukey post hoc test requires equal sample sizes, I use the Tukey-Kramer adjustment. The results of the ANOVA, in Table E.3, show that the conditions do not significantly affect product attractiveness ($F(2, 175) = 2.04$, $p > .05$). Despite the in-sample lower average of product attractiveness for the BDA condition, there is no significant difference between conditions according the ANOVA. Moreover, the ANOVA shows that most of the variance of product attractiveness is accounted for within groups. A Tukey post hoc test in Table E.4 reveals no significant differences between individual groups ($p > .05$).

Table E.3 ANOVA on Product Attractiveness

	Sum of Squares	df	Mean square	F.	Sig.
Between Groups	9.107	2	4.554	2.04	.1337
Within Groups	391.533	175	2.237		
Total	400.640	177	2.264		
Condition	**Mean**	**SD**			
Control	4.40	1.52			
Human-creativity	4.18	1.39			
BDA	3.85	1.59			
Total	4.14	1.50			

Table E.4 Tukey Post Hoc Multi Comparison Test on Product Attractiveness

Condition				95 % CI	
First condition	**Second condition**	**Mean difference (A-B)**	**Sig.**	**Lower Bound**	**Upper Bound**
Control	Human-creativity	-.220	0.706	-.872	.433
Control	BDA	-.557	0.117	-1.217	.103
Human-creativity	BDA	-.337	0.425	-.975	.300

Again, I perform an ANCOVA analysis where I control for gender, age, education, music knowledge, music preference, listening habits and willingness to provide information. Moreover, in order to see if significant effects exist of one of these independent variables on the dependent variable, I run a linear regression with the same control variables. Both are shown in Table E.5. The ANCOVA model shows that the residual still is substantial, but the amount of variance explained has increased a lot. The R-squared indicates that the variance explained in this model is reasonable (R^2 = .369). The ANCOVA model indicates that the BDA condition has a significant different mean for product attractiveness, than the control condition ($F(1,176) = 12.0$, $p < .01$). Moreover, the linear regression model shows that, ceteris paribus, the BDA condition finds the product significantly less attractive than the control condition ($\beta = -.66$, $p < .01$). The respondents in the BDA condition rate the product approximately 10% lower on a 1 to 7 scale, when controlled for several variables. Furthermore, the human-creativity condition does not significantly differ from the control condition in the ANCOVA ($p >.05$) and Linear models ($p >.05$). Besides, a few control variables have, ceteris paribus, a significant effect on product attractiveness. First, for every extra year of life of respondents, they rate the product significantly higher ($\beta = .11$, $p < .01$). Second, females rate the product significantly almost half a point higher than males ($\beta = .46$, $p < .05$). Third, the respondents who are fan of this specific type of music rate the song higher ($\beta = 1.53$, $p < .001$). As one could expect, this is the most substantial and highly significant effect in this model. Fourth, the willingness to provide information has a significant negative effect on product attractiveness (β = -.45, p < .05). This means that the less willing a person is to provide information, the lower he or she rates the product.

Table E.5 ANCOVA and Linear Regression Model on Product Attractiveness

Variables	**ANCOVA model (partial SS)**	**Linear regression model (coefficient and SE)**	
Human-creativity condition dummy	4.385	-.401	(.235)
BDA condition dummy	12.005**	-.658**	(.233)
Age	10.934**	.112**	(.042)
Gender	8.320*	.459*	(.196)
University	5.041	.455	(.249)
Music knowledge	.172	-.044	(.130)
Listening habit	1.453	.183	(.186)
Fan song	98.234***	1.527***	(.189)
Willingness to provide information	8.658*	-.451*	(.188)
Residual	253.019		
Model	147.621		
Constant		1.338	(1.202)
R-Squared	.369	.369	
F	10.89***	10.89***	
N	178	178	

Standard errors in parentheses for regression, control condition used as base-level
* p<0.05, ** p<0.01, *** p<0.001

Love. The created scale-variable 'contains love' is used to test if differences exist in the extent to which respondents perceive that products contain love, for different perceived production modes. Table E.6 shows that all conditions significantly deviate from normality (p > .05). Moreover, the homogeneity of variances assumption is not violated, according to the Levene's Test in Table E.7 (F (2, 175) = 1.36, p > .05).

Table E.6 Shapiro-Wilk W Test for Normal Data on Contains Love

Condition	**Obs.**	**W**	**V**	**z**	**Prob>z**
Control	55	.98136	.945	-.121	.54804
Human-creativity	63	.98227	1.003	.005	.49784
BDA	60	.98562	.782	-.531	.70241

Table E.7 Levene's Test for Homogeneity of Variances on Contains Love

	Levene statistic	**df1**	**df2**	**Sig.**
Levene's test using the mean	1.357	2	175	.260
Levene's test using the median	1.376	2	175	.255
Levene's test using the 10% trimmed mean	1.316	2	175	.271

Because the assumptions for parametric tests are not violated, I run a 3x1 one-way independent ANOVA on 'contains love' and the condition variable. Afterwards, I run a Tukey post hoc test, with Tukey-Kramer adjustment, to compare differences between conditions. The results of the ANOVA, in Table E.8, show that the conditions do not significantly affect a ‘contains love’ in the product. ($F(2, 175) = 2.85$, $p > .05$). A Tukey post hoc test in Table E.9 reveals no significant differences between all groups ($p > .05$).

Table E.8 ANOVA on Contains Love

	Sum of Squares	Df	Mean square	F.	Sig.
Between Groups	5.445	2	2.722	1.85	.1608
Within Groups	257.983	175	1.474		
Total	263.429	177	1.488		
Condition	**Mean**	**SD**			
Control	4.27	1.14			
Human-creativity	3.93	1.14			
BDA	3.86	1.35			
Total	4.01	1.22			

Table E.9 Tukey Post Hoc Multi Comparison Test on Contains Love

Condition				95 % CI	
First condition	**Second condition**	**Mean difference (A-B)**	**Sig.**	**Lower Bound**	**Upper Bound**
Control	Human-creativity	-.335	0.295	-.865	.194
Control	BDA	-.411	0.168	-.947	.125
Human-creativity	BDA	-.076	0.936	-.593	.442

Because of the observed high level of heterogeneity within the groups, I perform an ANCOVA analysis where I control for gender, age, education, music knowledge, music preference, listening habits and willingness to provide information. Moreover, in order to see if significant effects exist of these independent variables on the dependent variable, I run a linear regression with the same control variables. Both are shown in Table E.10. The ANCOVA model shows that the amount of variance explained by the model has increased a lot, in comparison to the ANOVA, but the residual still is substantial. The R-squared indicates that the variance explained in this model is still weak ($R^2 = .196$). The ANCOVA model shows that both the BDA condition ($F(1,176) = 7.0$, $p < .05$) and the human-creativity condition ($F(1,176) = 5.3$, $p < .05$) have a significant different mean for ‘contains love”, than the control condition. Moreover, the linear regression model indicates, ceteris paribus, that both the BDA condition ($\beta = -.50$, $p < .05$) and human-creativity condition ($\beta = -.44$, $p < .05$) perceive significantly less love containing in the product than the control condition. Besides, a few control variables have, ceteris paribus, a significant effect on product attractiveness. First, for every extra year of life of respondents, they perceive significantly more ‘contains love’ in the product ($\beta = .10$, $p < .05$). Second, the respondents who are fan of this specific type of music perceive more ‘contains love’ in the song ($\beta = .89$, $p < .001$).

Table E.10 ANCOVA and Linear Regression Model on Contains Love

Variables	ANCOVA model (partial SS)	Linear regression model (coefficient and SE)	
Human-creativity condition dummy	5.316*	-.442*	(.215)
BDA condition dummy	7.018*	-.503*	(.213)
Age	10.934*	.098*	(.038)
Gender	8.298	-.021	(.179)
University	.167	.241	(.228)
Music knowledge	.241	-.052	(.119)
Listening habit	.059	-.037	(.171)
Fan song	33.222***	.888***	(.173)
Willingness to provide information	1.142	-.164	(.172)
Residual	211.905		
Model	263.429		
Constant		2.298*	(1.100)
R-Squared	.196	.196	
F	4.54***	4.54***	
N	178	178	

Standard errors in parentheses for regression, control condition used as base-level
* p<0.05, ** p<0.01, *** p<0.001

Moreover, the created scale-variable ‘Made with Love’ is used to test if differences exist in the extent to which products are perceived to be made with love, for different perceived production modes. Table E.11 shows that the BDA condition ($D(60) = .98$, $p > .05$) and control condition ($D(55) = .96$, $p > .05$) consist of significantly normal distributed data. However, the human-creativity condition ($D(60) = .92$, $p < .001$) significantly deviates from normality. Moreover, the homogeneity of variances assumption is not violated, according to the Levene’s Test in Table E.12 ($F(2, 175) = .82$, $p > .05$).

Table E.11 Shapiro-Wilk W Test for Normal Data on Made with Love

Condition	Obs.	W	V	Z	Prob>z
Control	55	.96362	1.845	1.314	.09449
Human-creativity	63	.92438	4.275	3.140	.00084
BDA	60	.97859	1.164	.327	.37193

Table E.12 Levene’s Test for Homogeneity of Variances on Made with Love

	Levene statistic	df1	df2	Sig.
Levene’s test using the mean	.820	2	175	.442
Levene’s test using the median	.671	2	175	.512
Levene’s test using the 10% trimmed mean	.797	2	175	.452

Because the assumptions for parametric tests were not highly violated, I run a 3x1 one-way independent ANOVA on contains love and the conditions variable. Afterwards, I run a Tukey post hoc test, with Tukey-Kramer adjustment, to compare differences between conditions. The results of the ANOVA, in Table E.13, show that conditions do significantly affect that the product is perceived to be made with love. ($F(2, 175) = 3.13$, $p < .05$). A Tukey post hoc test in Table E.14 reveals that this effect only is significant between the control and BDA conditions ($p < .05$). This effect shows that the BDA condition has a mean for made with love that is approximately half a point lower than the control condition ($M_{BDA} = 4.11$ versus $M_{control} = 4.67$). Therefore, respondents in the BDA condition perceive the product to be less made with love, than respondents in the control condition. There is no significant difference between the human-creativity and control condition, according to the ANOVA ($p > .05$).

Table E.13 ANOVA on Made with Love

	Sum of Squares	**Df**	**Mean square**	**F.**	**Sig.**
Between Groups	9.825	2	4.913	3.13	.0463
Within Groups	274.901	175	1.571		
Total	284.726	177	1.609		
Condition	**Mean**	**SD**			
Control	4.67	1.20			
Human-creativity	4.51	1.18			
BDA	4.11	1.37			
Total	4.43	1.27			

Table E.14 Tukey Post Hoc Multi Comparison Test on Made with Love

Condition				**95 % CI**	
First condition	**Second condition**	**Mean difference (A-B)**	**Sig.**	**Lower Bound**	**Upper Bound**
Control	Human-creativity	-.165	0.756	-.712	.382
Control	BDA	-.564	0.044	-.1.117	-.011
Human-creativity	BDA	-.400	0.184	-.934	.135

Because of the observed high level of heterogeneity within the groups, I perform an ANCOVA analysis, in order to see if the effect holds while I control for gender, age, education, music knowledge, music preference, listening habits and willingness to provide information. Moreover, in order to see if significant effects exist of these independent variables on the dependent variable, I run a linear regression with the same control variables. Both are shown in Table E.15. The ANCOVA model shows that the amount of variance explained by the model has increased a lot, in comparison to the ANOVA, but the residual still is substantial. The R-squared indicates that the variance explained in this model is still weak (R^2 = .157). The ANCOVA model shows that the BDA condition has a significant different mean for made with love, than the control condition (F (1,176) = 8.2, p < .05). Moreover, the linear regression model indicates, ceteris paribus, that the BDA condition (β = -.54, p < .05) perceives significantly less that the song is made with love than the control condition. There is no difference in mean and effect between the human-creativity condition and the control condition (p > .05). Besides, there is only one control variable that has a significant effect on the product being perceived as made with love. Respondents who are fan of this specific type of music perceive more that the song is made with love (β = .72, p < .001).

Table E.15 ANCOVA and Linear Regression Model on Made with Love

Variables	**ANCOVA model (partial SS)**	**Linear regression model (coefficient and SE)**	
Human-creativity condition dummy	.535	-.140	(.229)
BDA condition dummy	8.156*	-.542*	(.227)
Age	1.298	.029	(.041)
Gender	.287	.085	(.190)
University	4.290	-.420	(.242)
Music knowledge	1.481	-.129	(.126)
Listening habit	.0367	.029	(.182)
Fan song	21.827***	.720***	(.184)
Willingness to provide information	.026	-.025	(.183)
Residual	240.181		
Model	284.727		
Constant		4.047***	(1.171)
R-Squared	.157	.157	
F	3.46***	3.46***	
N	178	178	

Standard errors in parentheses for regression, control condition used as base-level
* p<0.05, ** p<0.01, *** p<0.001

Creativity. The created scale-variable 'Creativity' is used to test if differences exist in perceived creativity in products, for different perceived production modes. Table E.16 shows that all conditions significantly deviate from normality (p > .05). Moreover, the homogeneity of variances assumption is not violated, according to the Levene's Test in Table E.17 (F (2, 175) = 0.74, p > .05).

Table E.16 Shapiro-Wilk W Test for Normal Data on Creativity

Condition	**Obs.**	**W**	**V**	**z**	**Prob>z**
Control	55	.97766	1.133	.267	.39459
Human-creativity	63	.97944	1.162	.324	.37280
BDA	60	.96140	2.098	1.597	.05511

Table E.17 Levene's Test for Homogeneity of Variances on Creativity

	Levene statistic	**df1**	**df2**	**Sig.**
Levene's test using the mean	.074	2	175	.928
Levene's test using the median	.076	2	175	.927
Levene's test using the 10% trimmed mean	.096	2	175	.909

Because the assumptions for parametric tests are not violated, I run a 3x1 one-way independent ANOVA on creativity and the condition variable. Afterwards, I run a Tukey post hoc test, with Tukey-Kramer adjustment, to compare differences between groups. The results of the ANOVA, in Table E.18, show that conditions do not significantly affect the perceived creativity in the product. ($F(2, 175) = 0.44$, $p > .05$). A Tukey post hoc test in Table E.19 reveals no significant differences between all groups ($p > .05$).

Table E.18 ANOVA on Creativity

	Sum of Squares	df	Mean square	F.	Sig.
Between Groups	1.285	2	.642	0.44	.6452
Within Groups	255.810	175	1.461		
Total	257.094	177	1.453		
Condition	**Mean**	**SD**			
Control	3.52	1.24			
Human-creativity	3.50	1.19			
BDA	3.69	1.20			
Total	3.57	1.21			

Table E.19 Tukey Post Hoc Multi Comparison Test on Creativity

Condition				95 % CI	
First condition	**Second condition**	**Mean difference (A-B)**	**Sig.**	**Lower Bound**	**Upper Bound**
Control	Human-creativity	-.018	0.996	-.546	.509
Control	BDA	.169	0.734	-.364	.703
Human-creativity	BDA	.188	0.666	-.328	.703

Because of the observed high level of heterogeneity within the groups, I perform an ANCOVA analysis, in order to see if the effect holds while I control for gender, age, education, music knowledge, music preference, listening habits and willingness to provide information. Moreover, in order to see if significant effects exist of these independent variables on the dependent variable, I run a linear regression with the same control variables. Both are shown in Table E.20. The ANCOVA model shows that the amount of variance explained by the model has increased a lot, in comparison to the ANOVA, but the residual still is substantial. The R-squared indicates that the variance explained in this model is reasonable ($R^2 = .351$). The ANCOVA model shows that both the BDA condition ($F(1,176) = .8$, $p > .05$) and human-creativity condition ($F(1,176) = .1$, $p > .05$) have no significant different mean for creativity, than the control condition. Moreover, the linear regression model indicates, ceteris paribus, that both the treatments do not significantly differ in perceived creativity to the control condition ($p > .05$). In this model, creativity is partly explained by two control variables. First, respondents with more knowledge of music rate the product significantly less creative ($\beta = -.26$, $p < .05$). Second, respondents who are fan of this specific type of music rate the song as more creative ($\beta = 1.29$, $p < .001$). The latter explains a large effect, respondents who are a fan, rate the song on average 1.29 higher on creativity on a 1 to 7 scale.

Table E.20 ANCOVA and Linear Regression Model on Creativity

Variables	**ANCOVA model (partial SS)**	**Linear regression model (coefficient and SE)**	
Human-creativity condition dummy	.065	-.049	(.191)
BDA condition dummy	.769	.167	(.189)
Age	1.305	.039	(.034)
Gender	1.761	.211	(.159)
University	.184	.087	(.202)
Music knowledge	6.130*	-.262*	(.105)
Listening habit	.000	.003	(.151)
Fan song	70.385***	1.29***	(.154)
Willingness to provide information	.298	-.084	(.153)
Residual	166.756		
Model	257.094		
Constant		2.771**	(.976)
R-Squared	.351	.351	
F	10.1***	10.1***	
N	178	178	

Standard errors in parentheses for regression, control condition used as base-level
* p<0.05, ** p<0.01, *** p<0.001

Privacy. The variable 'Privacy concerns 1' is used to test if differences exist in perceived privacy concerns for the product, for different perceived production modes. Table E.21 shows that only the BDA condition consists of significantly normal distributed data ($D(60) = .97$, $p > .05$). The control condition ($D(55) = .92$, $p < .001$) and the human-creativity condition ($D(63) = .92$, $p < .001$) significantly deviate from normality. However, the homogeneity of variances assumption is not violated, according to the Levene's Test in Table E.22 ($F(2, 175) = 1.09$, $p > 0.05$).

Table E.21 Shapiro-Wilk W Test for Normal Data on Privacy Concerns 1

Condition	**Obs.**	**W**	**V**	**Z**	**Prob>z**
Control	55	.91617	4.251	3.104	.00096
Human-creativity	63	.91916	4.570	3.284	.00051
BDA	60	.97205	1.519	.901	.18373

Table E.22 Levene's Test for Homogeneity of Variances on Privacy Concerns 1

	Levene statistic	**df1**	**df2**	**Sig.**
Levene's test using the mean	1.088	2	175	.339
Levene's test using the median	1.889	2	175	.154
Levene's test using the 10% trimmed mean	1.703	2	175	.185

I run a 3x1 one-way independent ANOVA on privacy concerns and the condition variable. Afterwards, I ran a Tukey post hoc test to compare differences between conditions. Because the normal Tukey post hoc test requires equal sample sizes, I use the Tukey-Kramer adjustment. The results of the ANOVA, in table E.23, show the individual means for conditions. These means are low, considered it is a 1-7 scale. Therefore, respondents in general perceive low privacy concerns. The ANOVA indicates that statistical differences exist between conditions ($F(2, 175) = 3.23$, $p < .05$). However, a Tukey post hoc test in Table E.24 reveals no significant differences between specific conditions ($p > .05$). The ANOVA test in Table E.23 shows that most of the variance is explained within groups. This indicates that there is a lot of heterogeneity within each conditions.

Table E.23 ANOVA on Privacy Concerns 1

	Sum of Squares	**df**	**Mean square**	**F.**	**Sig.**
Between Groups	13.498	2	6.749	3.23	.0420
Within Groups	365.946	175	2.091		
Total	365.946	177	2.144		
Condition	**Mean**	**SD**			
Control	2.42	1.34			
Human-creativity	2.52	1.40			
BDA	3.05	1.58			
Total	2.67	1.46			

Table E.24 Tukey Post Hoc Multi Comparison Test on Privacy Concerns 1

Condition				**95 % CI**	
First condition	**Second condition**	**Mean difference (A-B)**	**Sig.**	**Lower Bound**	**Upper Bound**
Control	Human-creativity	.106	0.917	-.525	.736
Control	BDA	.632	0.053	-.006	1.27
Human-creativity	BDA	.526	0.111	-.090	1.14

Because of the substantial amount of heterogeneity within groups, I perform an ANCOVA analysis where I control for gender, age, education, music knowledge, music preference, listening habits and if people recognized the song. Moreover, in order to see if significant effects exist of these independent variables on the dependent variable, I run a linear regression with the same control variables. Both are shown in Table E.25. The ANCOVA model shows that the residual still is substantial and the model explains a very small amount of the variance of the privacy variable. This is also indicated by the low R-squared for both models, which are very weak ($R^2 = .05$). The ANCOVA model shows that the BDA condition has a significant different mean for privacy concerns, than the control condition (F (1,176) = 9.8, p < .05). Moreover, the linear regression model indicates, ceteris paribus, that the BDA condition has significantly more privacy concerns about the production process than the control condition (β = .60, p < .05). The human-creativity condition does not differ from the control condition in both models (p > .05). Moreover, only the variable which indicates that respondents state they recognized the song has, ceteris paribus, a significant influence on the perceived privacy concerns (β = .65, p < .05). Even in a model – regression model 2 – run on the underlying variables of 'willingness to give information', no other variables have a significant effect (p > .05).

Table E.25 ANCOVA and Linear Regression Model on Privacy Concerns 1

Variables	**ANCOVA model (partial SS)**	**Linear regression model 1 (coefficient and SE)**		**Linear regression model 2 (coefficient and SE)**	
Human-creativity condition dummy	.358	.115	(.277)	.125	(.278)
BDA condition dummy	9.843*	.596*	(.275)	.631*	(.278)
Age	1.534	.042	(.049)	.044	(.049)
Gender	.331	.092	(.231)	.057	(.235)
University	.722	-.172	(.294)	-.205	(.295)
Music knowledge	.152	-.041	(.153)	-.010	(.155)
Listening habit	.000	.001	(.220)	.027	(.222)
Fan song	1.890	-.212	(.223)	-.166	(.225)
Recognize the song	10.501*	.647*	(.289)	.688*	(.295)
Willingness to provide information	1.296	-.174	(.222)		
To provide age				-.335	(.176)
To provide 2 favorite songs				.162	(.182)
To provide payment methods				-.061	(.135)
To provide phone number				.137	(.189)
To provide annual income				.021	(.179)
Residual	349.978				
Model	379.444				
Constant		2.134	(1.421)	1.377	(1.483)
R-Squared	.078	.078		.099	
F	1.41	1.41		1.28	
N	178	178		178	

Standard errors in parentheses for regression, control condition used as base-level
* p<0.05, ** p<0.01, *** p<0.001

Because the assumptions for parametric tests were somewhat violated, I run the non-parametric Kruskal-Wallis Test as a control for robustness. The outcome of this test, in Table E.26, shows that there was no significant difference between the different conditions in for privacy concerns (H(2) = 5.757, p > .05). However, because there is a significant difference at the p < .10 level, I check for differences between individual conditions using Mann-Whitney tests. Table E.27 shows a significant difference in privacy concerns between the BDA condition and the rest of the sample data ($z = -2.366$, $p < .05$). This condition has significantly more privacy concerns.

Table E.26 Kruskal-Wallis Equality-of-Populations Rank Test on Privacy Concerns 1

Condition	Obs.	Rank Sum	Mean Rank
Control	55	4467	81.22
Human-creativity	63	5348.5	84.90
BDA	60	6115.5	101.93
Test Statistics	Chi-squared	df.	Prob.
With ties in data	5.757	2	.06

Table E.27 Mann-Whitney Rank-Sum Test on Privacy Concerns 1

Condition	Obs.	Rank Sum	Mean Rank
BDA	60	6115.5	101.93
Rest of sample data	118	9815.5	83.18
Test Statistics	Z	df.	Prob.
With ties in data	-2.366	2	.02

8.6. Appendix F: Mediation analyses

First, I give a short introduction to the analyses of mediation effects. The most well-known research on mediation effects is the paper of Baron and Kenny (1986). They state that:" a given variable may be said to function as a mediator to the extent that it accounts for the relation between the predictor and the criterion." They introduce a path diagram, which is shown in Figure F.1.

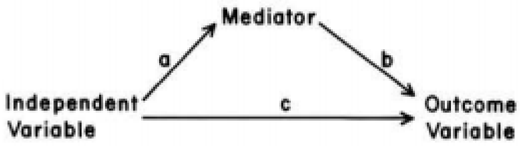

Figure F.1 Mediation Path Diagram from Baron and Kenny (1986)

This diagram shows that the outcome variable, which is product attractiveness in my research, is caused by two paths. First, a direct effect of the independent variable – the condition variable –, which is path c. Second, an effect of the mediators – in my research I hypothesize love, creativity and privacy concerns – on the product attractiveness, indicated by path b. Moreover, path a shows the effect of the condition variable on the mediators. Thus, in order to indicate a variable as a mediator, it must meet the following conditions, according to Baron and Kenny (1986): "(a) variations in levels of the independent variable significantly account for variations in the presumed mediator (i.e., path c), (b) variations in the mediator significantly account for variations in the dependent variable (i.e., path b), and (c) when paths a and b are controlled, a previously significant relation between the independent and dependent variables is no longer significant, with the strongest demonstration of mediation occurring when path c is zero". This means that if path c is reduced to zero, the presence of single dominant mediator is highly likely. However, in my research I propose three mediators and therefore I should control the proposed mediators on if they significantly decrease the effect of path c.

Although many researchers used the approach of Baron and Kenny (1986) in the past, this approach is outperformed nowadays by newer approaches and there is increasing criticisms on their approach (Zhao et al. 2010). Zhao et al. (2010) describe that the Preacher and Hayes (2004) bootstrapping test is the most accepted approach at the moment. The bootstrapping test is used to measure the indirect effect (a X b) and is more powerful than the Sobel's test that is used to measure the indirect effect in the Baron and Kenny (1986) method. Furthermore, Preacher and Hayes (2008) modified their method to a version which allows to test for multiple mediators simultaneously. This method allows to add covariates as well, which might me be needed in my case, because of the earlier observed influence of music preferences.

Preacher and Hayes (2008) state four reasons why it is better to run one multiple mediation model than separate simple mediation models for each mediator individually. First, in the multiple mediation model it is possible to conclude that the set of proposed mediators indeed mediates the effect of the dependent on the independent variable, if an effect is found. Second, the other proposed mediators are presence in the determination of the extent to which a mediation effect of an variable exists. Third, there is less change of getting biased parameter estimates, because the omitted variable problem, as described by Judd and Kenny (1981), is reduced in a multiple mediation model. Fourth, the importance of different theories can be compared, because the model gives the relative importance of the indirect effects of the mediators. The only drawback of multiple mediation that Preacher and Hayes (2008) state, is that these models can be more complex than simple mediation models. However, they do state the following important note: “It is important to remember that a specific indirect effect through a mediator in the multiple mediation context is not the same as the indirect effect through this mediator alone, except in the unlikely circumstance that all other mediators are uncorrelated with the mediator.” Thus, the outcomes of the multiple mediation model must be interpreted in the context of the other proposed mediators.

Figure F.2 shows the multiple mediation design for my study, which is an filled in version of Figure 2 of Preacher and Hayes (2008). Actually, Figure F.2 is quite similar to my conceptual framework (Figure 2) and therefore I expect that this approach fits my research well.

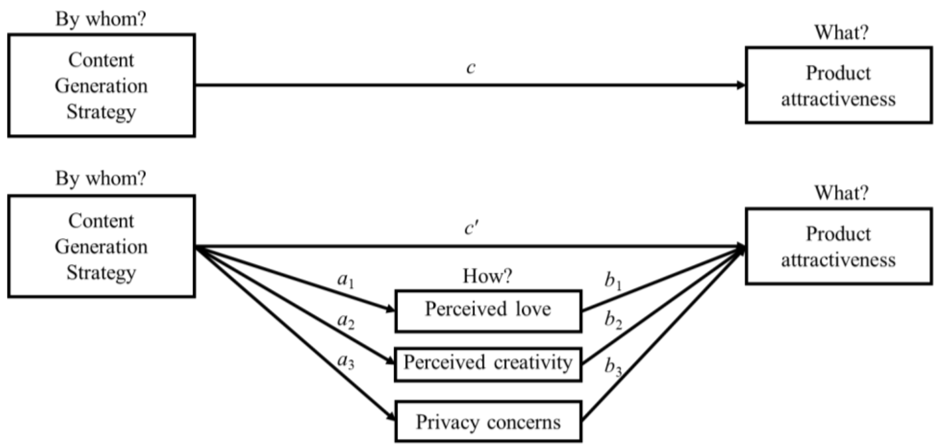

Figure F.2 Multiple Mediation Design, based on Preacher and Hayes (2008).

Figure F.2 consists of two parts. The upper part represents the total effect of the content generation strategy on the product attractiveness (path c). The lower part represents shows the indirect effects between the content generation strategy on the product attractiveness via the mediators – love (path a_1 & b_1), creativity (path a_2 & b_2) and privacy concerns (path a_3 & b_3) –, and the direct effect of the content generation strategy on the product attractiveness (path c′) as well. In this case, the indirect effect of a mediator is quantified as a X b and the total indirect effect consists of the sum of the a X b's of all mediators. The total effect (path c), as shown in the upper part of Figure F.2, is the sum of the direct (path c′) and the total indirect effect (a_1 X b_1 + a_2 X b_2 + a_3 X b_3). This means that a situation can exist where the total indirect effect is not significantly different from zero, while individual mediation effects do exist. For example, in my research I expect a negative mediation effect of privacy concerns and positive mediation effects of love and creativity. If these effects exist, they might cancel each other out, which can result in an insignificant total indirect effect.

Preacher and Hayes (2004, 2008) only provide their macros for SAS and SPPS, and do not provide a version for STATA. Therefore, I use a similar approach that is modified for STATA and follows the same steps (UCLA 2018). This method consists of the following steps. First, the direct and indirect effects are tested with a seemingly unrelated regression. It is possible to include control variables in this regression. Second, nonlinear combinations of estimators are done, to obtain more reliable indirect effect parameter values. Third, these indirect effect parameter values are bootstrapped, which leads to more trustworthy outcomes. The presented bootstrap estimates are based on 5,000 bootstrap samples, as recommended by Preacher and Hayes (2008). Furthermore, I present the estimates with three types of confidence intervals (CI): percentile (Perc.) CI, bias corrected (BC) CI, bias corrected and accelerated (BCa) CI. These CI are seen as more reliable in this type of research than simple Z statistic, because the latter does not handle well the skewness in the distribution of mediator effects (Zhao et al. 2010).

Multiple mediation. I run two multiple mediation models. First, I run a multiple mediation model with the dummy variable of the human-creativity condition as independent variable and add several control variables. Second, I run a multiple mediation model with the dummy variable of the BDA condition as independent variable and add several control variables.

Table F.1 Multiple Mediation: Seemingly Unrelated Regression Models

Variables	**Multiple mediation Model on Human-creativity condition dummy**			**Multiple mediation Model on BDA condition dummy**	
Contains love					
Age	.081*	(.037)		.084*	(.037)
Gender	-.009	(.176)		-.062	(.174)
University	.190	(.224)		.199	(.223)
Music knowledge	-.048	(.117)		-.084	(.115)
Listening habit	-.038	(.168)		.008	(.167)
Fan song	.887***	(.171)		.883***	(.170)
Recognize the song	-.180	(.221)		-.149	(.220)
Willingness to provide information	-.147	(.169)		-.170	(.169)
a_1: Human-creativity condition dummy	**-.181**	**(.180)**	**BDA condition dummy**	**-.264**	**(.178)**
Constant	2.416*	(1.087)		2.372*	(1.083)
Creativity					
Age	.040	(.032)		.033	(.032)
Gender	.221	(.154)		.217	(.152)
University	.087	(.195)		.068	(.194)
Music knowledge	-.257*	(.102)		-.261**	(.101)
Listening habit	.014	(.146)		.017	(.145)
Fan song	1.281***	(.149)		1.282***	(.148)
Recognize the song	-.305	(.192)		-.310	(.192)
Willingness to provide information	-.086	(.147)		-.082	(.147)
a_2: Human-creativity condition dummy	**-.151**	**(.157)**	**BDA condition dummy**	**.207**	**(.155)**
Constant	2.849**	(.946)		2.876**	(.944)
Privacy concerns					
Age	.059	(.048)		.045	(.047)
Gender	.085	(.227)		.104	(.222)
University	-.120	(.287)		-.163	(.284)
Music knowledge	-.043	(.150)		-.032	(.147)
Listening habit	.006	(.216)		-.012	(.212)
Fan song	-.217	(.219)		-.212	(.216)
Recognize the song	.669*	(.284)		.644*	(.280)
Willingness to provide information	-.193	(.218)		-.173	(.215)
a_3: Human-creativity condition dummy	**-.202**	**(.231)**	**BDA condition dummy**	**.536***	**(.227)**
Constant	2.055	(1.396)		2.129	(1.378)
Product attractiveness					
b_1: Contains love	**.401*****	**(.080)**		**.366*****	**(.080)**
b_2: Creativity	**.225***	**(.092)**		**.259****	**(.092)**
b_3: Privacy concerns	**.086**	**(.057)**		**.107**	**(.056)**
Age	.047	(.037)		.058	(.036)
Gender	.414*	(.172)		.372*	(.168)
University	.311	(.218)		.351	(.214)
Music knowledge	.039	(.116)		.027	(.112)
Listening habit	.187	(.163)		.214	(.159)
Fan song	.908***	(.199)		.894***	(.195)
Recognize the song	.054	(.219)		.072	(.215)
Willingness to provide information	-.336*	(.165)		-.356*	(.162)
c′: Human-creativity condition dummy	**.073**	**(.176)**	**BDA condition dummy**	**-.462****	**(.176)**
Constant	-.358	(1.089)		-.482	(1.070)

Standard errors in parentheses for regression,
* p<0.05, ** p<0.01, *** p<0.001

Table F.2 Multiple Mediation: Bootstrapping Analysis of Indirect Effects

	Point Estimate	Product of Coefficients		Bootstrapping					
				Perc. 95% CI		BC 95% CI		BCa 95% CI	
		SE	Z	Lower	Upper	Lower	Upper	Lower	Upper
Indirect effects model Human-creativity condition dummy									
Contains love	-.073	.077	-.94	-.232	.080	-.249	.067	-.250	.066
Creativity	-.034	.040	-.86	-.125	.035	-.147	.021	-.149	.020
Privacy concerns	-.017	.027	-.65	-.082	.025	-.108	.013	-.108	.013
TOTAL	-.124	.104	-1.19	-.339	.082	-.354	.065	-.356	.065
Indirect effects model BDA condition dummy									
Contains love	-.097	.076	-1.27	-.263	.041	-.267	.038	-.268	.038
Creativity	.054	.046	1.17	-.024	.154	-.014	.176	-.013	.176
Privacy concerns	.057	.040	1.43	-.004	.151	**.006**	**.184**	**.006**	**.187**
TOTAL	.014	.111	.13	-.211	.226	-.195	.247	-.195	.247

5,000 bootstrap samples, Perc.: percentile, BC: bias corrected, BCa: bias corrected and accelerated

The results of the seemingly unrelated regression are provided in Table F.1 and the bootstrapping estimates of the effects are shown in Table F.2. The seemingly unrelated regressions shows, ceteris paribus, that there is no significant effect of the human-creativity condition dummy on the mediators ‘contains love”, creativity and privacy concerns ($p > .05$). Furthermore, the human-creativity condition dummy has, ceteris paribus, no significant direct effect (c′) on product attractiveness ($p > .05$). However, in earlier analyses I found that the control condition perceives the production process as solely human-creativity as well, because this is the default. As both conditions do not differ that much, and half of the data to which the human-creativity condition dummy is compared consists of this control condition, it makes sense that again I find no effects of the human-creativity condition dummy. For the model with the human-creativity condition dummy, I do find, ceteris paribus, positive significant effects of ‘contains love’ (b_1; $\beta = .40$, $p < .001$) and creativity (b_2; $\beta = .23$, $p < .05$) on product attractiveness. The bootstrapping test, as one might expect, based on the results of the regression, shows that there are no mediation effects of the human-creativity condition on the product attractiveness ($p > .05$). Again, I propose this is due to that human-creativity produced products are still the default.

Therefore, I look at the BDA condition dummy model, to see if this condition, which is compared to both the human-creativity and control condition, has any mediation effects on product attractiveness. The seemingly unrelated regression shows, ceteris paribus, a negative significant direct effect (c′) on product attractiveness ($\beta = -.46$, $p < .01$). Furthermore, I find, ceteris paribus, a significant positive effect of the BDA condition on privacy concerns (a_3; $\beta = .54$, $p < .05$). Moreover, the regression shows, ceteris paribus, positive effects of 'contains love' (b_1; $\beta = .37$, $p < .001$) and creativity (b_2; $\beta = .26$, $p < .01$) on product attractiveness, but no significant effect of privacy concerns on product attractiveness (b_3; $p > .05$). Thus, none of the mediators has both a significant path 1 and 2 in the seemingly unrelated regression, for the BDA condition. In order to see if mediation effects exist, I perform a bootstrapping analysis. This analysis shows that there is a significant positive indirect mediation effect of privacy concerns (a_3 X b_3) on the effect of the BDA condition on the product attractiveness ($\beta = .06$, [$CI_{Perc., 95\%}$]: -.00, .15; [$CI_{BC., 95\%}$]: .01, .18; [$CI_{BCa., 95\%}$]: .01, .19). This positive effect is of particular interest, because I already found a positive effect from the BDA condition on privacy concerns (a_3) in the regression and therefore the effect of privacy concerns on product attractiveness (b_3) must be positive as well, because both multiplied (a_3 X b_3) produces a positive effect. However, the b_3 effect is very small, because both (1) the multiplication is just above zero while a_3 is significantly large and (2) the regression find no significant b_3. Therefore, this mediation shows that privacy concerns increase with the use of BDA in the production process, although this does not lead to lower product attractiveness.

Sequential mediation. For the mediator love, I perform sequential mediation as well. This is in line with Fuchs et al. (2015), who found that the mediation of love in their handmade effect consists of two stages, which caused the mediation to be sequential. Figure F.3 shows the design of this mediation, where effect a_1 is split up in $a_{1,1}$ and $a_{1,2}$, because 'made with love' is expected to be a mediator between how a product is produced and if respondents perceive it contains love.

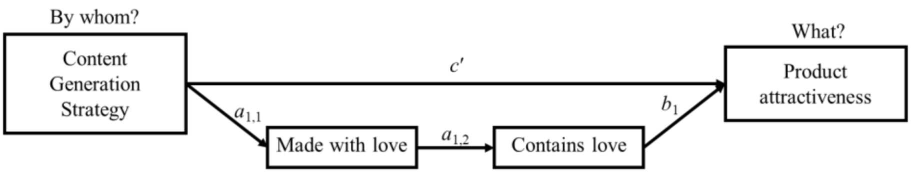

Figure F.3 Sequential Mediation Design

In total, I run two sequential mediation models. First, I run a sequential mediation model with the dummy variable of the human-creativity condition as independent variable, including the control variables. Second, I run a sequential mediation model with the dummy variable of the BDA condition as independent variable, including the control variables. The results of the seemingly unrelated regression are provided in Table F.3. I find no significant direct effect (c′) on product attractiveness from the Human-creativity condition (β = -.01, p > .05) and from the BDA condition (β = -.27, p > .05). However, I did find this effect in the multiple mediation model, where creativity and privacy concerns are included as well. This indicates that the sequential mediation through ‘made with love’ and ‘contains love’ explains the whole human-creativity effect.

Table F.3 Sequential Mediation: Seemingly Unrelated Regression Models

Variables	**Sequential mediation Model on Human-creativity condition dummy**			**Sequential mediation Model on BDA condition dummy**	
Made with love					
Age	.022	(.040)		.033	(.039)
Gender	.097	(.188)		.075	(.184)
University	-.474*	(.238)		-.437	(.235)
Music knowledge	-.125	(.125)		-.138	(.122)
Listening habit	-.027	(.179)		.046	(.176)
Fan song	.720***	(.182)		.715***	(.179)
Recognize the song	-.160	(.235)		-.136	(.232)
Willingness to provide information	-.007	(.181)		-.026	(.178)
$a_{1,1}$: Human-creativity condition dummy	**.142**	**(.192)**	**BDA condition dummy**	**-.462***	**(.188)**
Constant	4.163***	(1.087)		4.099***	(1.141)
Contains love					
$a_{1,2}$: Made with love	**.457*****	**(.061)**		**.448*****	**(.063)**
Age	.072*	(.032)		.069*	(.033)
Gender	-.053	(.154)		-.096	(.154)
University	.406*	(.198)		.395*	(.199)
Music knowledge	.009	(.102)		-.023	(.102)
Listening habit	-.051	(.147)		-.013	(.147)
Fan song	.558***	(.156)		.563***	(.157)
Recognize the song	-.107	(.193)		-.088	(.194)
Willingness to provide information	-.144	(.148)		-.158	(.149)
Human-creativity condition dummy	**-.246**	**(.158)**	**BDA condition dummy**	**-.057**	**(.160)**
Constant	.512	(.983)		.536	(.989)
Product attractiveness					
b_1: Contains love	**.372*****	**(.084)**		**.369*****	**(.083)**
Made with love	**.202****	**(.079)**		**.184***	**(.079)**
Age	.059	(.037)		.065	(.037)
Gender	.451**	(.172)		.426*	(.170)
University	.422	(.223)		.431	(.222)
Music knowledge	.001	(.114)		-.019	(.113)
Listening habit	.184	(.164)		.208	(.162)
Fan song	1.057***	(.180)		1.070***	(.179)
Recognize the song	.070	(.216)		.087	(.215)
Willingness to provide information	-.375*	(.166)		-.390*	(.165)
c′: Human-creativity condition dummy	**-.013**	**(.177)**	**BDA condition dummy**	**-.265**	**(.176)**
Constant	-.313	(1.099)		-.271	(1.093)

Standard errors in parentheses for regression
* p<0.05, ** p<0.01, *** p<0.001

Furthermore, the bootstrapping estimates of the indirect effects are shown in Table F.4. Effect 1 to 3 indicate the individual effects ($a_{1,1}$, $a_{1,2}$, and b_1) and the total effect indicates the sequential effect ($a_{1,1}$ X $a_{1,2}$, X b_1). It was not possible to obtain BCa CI's, therefore I only use the Perc. CI and BC CI as measures for significance. The results of the bootstrapping show, in line with Fuchs et al. (2015) that there is a significant sequential indirect effect from the production mode to 'made with love' to 'contains love' to product attractiveness for the BDA condition (β = -.08, [$CI_{Perc., 95\%}$]: -.17, -.01; [$CI_{BC., 95\%}$]: -.18, -.02). For the human-creativity condition dummy I find no such effect. However, this is due to the earlier noted reason of human creativity still being the default production mode.

Table F.4 Sequential Mediation: Bootstrapping Analysis of Indirect Effects

	Point Estimate	Product of Coefficients		Bootstrapping					
				Perc. 95% CI		BC 95% CI		BCa 95% CI	
		SE	Z	Lower	Upper	Lower	Upper	Lower	Upper
Indirect effects Human-creativity condition dummy									
Effect 1	.065	.089	.73	-.104	.248	-.105	.247	BCa CI not obtained	
Effect 2	.029	.043	.67	-.048	.123	-.040	.134		
Effect 3	-.091	.064	-1.43	-.229	.027	-.246	.014		
TOTAL sequential effect	-.024	.034	.70	-.038	.099	-.035	.102		
Indirect effects BDA condition dummy									
Effect 1	-.207*	.093	-2.23	**-.394**	**-.030**	**-.409**	**-.043**	BCa CI not obtained	
Effect 2	-.085	.048	-1.76	**-.194**	**-.005**	**-.224**	**-.017**		
Effect 3	-.021	.063	-.34	-.149	.105	-.150	.104		
TOTAL sequential effect	-.076	.040	-1.92	**-.166**	**-.009**	**-.184**	**-.018**		

5,000 bootstrap samples, Perc.: percentile, BC: bias corrected, BCa: bias corrected and accelerated

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