Emotion,
Cultural Valuation of Being Human and
AI Services

Abstract

This study alerts that successful AI services depend not only on the improvement of the ability of AI to understand customers' emotions, but also on whether the utility function of the customer allows for the perfect substitution between an AI- and a human-delivered service. We argue that the utility function of customers includes the subjective valuation of being human, which AI services cannot meet by nature. A Culture Based Development (CBD) model for the transformation of emotions into feelings and order of preferences is offered to explain the cultural valuation of being human as a component of customers' utility function. Using primary data from an experimental survey and employing two alternative machine learning algorithms (Lasso and Random Forest), we operationalize our CBD model to show that the estimation efficiency of the AI algorithms cannot compensate for the omission of the cultural valuation of being human from the modelling of the utility function of the customer.

Key words: culture, emotion, feelings, perception, preferences, creative services

JEL: Z10, D01, D11, D12, D91, L80

Introduction

Interaction between human beings is an element of every service[1] delivered by a human being, and this interaction is valued by the consumers of the services (Boshoff 2012; Lin, Chi and Gremler 2019). People bestow importance to being human (see Khalil 2004; Fisher 2021) and hence value interaction with humans. This psychological fact of life is known across many disciplines, but it is still insufficiently incorporated in economic models about human decision making (Bechara and Damasio 2005; Alsharif et al. 2021). The problem narrows down to incorporating emotion in the micro-economic model of human satisfaction-formation and decision making.

The emotion-wise insufficiency of the existing economic models is of particularly eminent importance in the age of transition to an artificial intelligence (AI) based servitization of the economy (see Vlačić et al. 2021). We argue this is so in two ways. First, mostly economists advice policy makers and businesses on the transition from human service-delivery to the AI-based delivery of services in the future. Economists' efforts (in line with AI developers' efforts) have been focused on the AI service becoming so efficient and human-like that it can perfectly substitute human labour, including in services (Frey and Osborne 2017). Since the AI developers' efforts are growingly successful, economists are likely to highly overestimate the satisfaction of customers with the highly efficient AI-services as substitutes for their human-delivered alternative. This will happen if economists do not account for the importance of being human and the lost human interaction as a crucial part of the substitution between human and AI service delivery (Mattila and Enz 2002; Tremblay et al. 2016; Pelau et al. 2021; Haesevoets et al. 2021). Second, artificial intelligence itself, when created for the purpose of delivering services, is created with the purpose to optimize customer satisfaction. The data that these AI use (to observe and be trained on) is often collected by economists who used to monitor and study customer satisfaction in economic ways (see Poria et al. 2019). Thus, the economically-reasoned data collection process is clearly likely to affect the learning of the AI. If the data is collected without factoring accurately the information about the importance of being human, the AI will only replicate some biases in the data but will not predict precisely the human response to its own replication. That is why we argue that elaborating a way to adequately account for emotions in a micro-economic model for customer satisfaction is pivotal to enabling the successful transition from human-based to AI-based services.

This study focuses on the question whether the emotional significance of the importance of being human can be precisely accounted for by an AI algorithm if the economic data offered to the AI (for training its understanding about the customer satisfaction) does not account for the fact that this emotion is part of the customer's utility function. To address this question, we first provide a conceptual micro-economic model for customer valuation of services. This model contains the necessary augmentation of the micro-economic model of customer decision making, inspired by multidisciplinary literature on emotion. This model is offered in order to help the reader identify what is the nature of the problem when emotions (and in particular the emotion regarding the importance of being human) are not accurately accounted for. Second, we employ a dataset, previously

[1] Human interaction is shared co-experience of humans in time (Lim et al. 2012). It is likely that the importance of being human is satisfied also by man-made goods, as according to Karl Marx, human time was congealed in the products of human labour per se. Marx put this himself as follows: 'commodities are only definite masses of congealed labour-time' (Marx, 1983: 47; Marx, 1987a: 272). This implies that products can carry in a congealed and delayed in time form the co-experience between humans that produced and consumed the good. Thus, the co-experience that is fundament of social interaction can be delivered by human made goods in a 'preserved in a can' form.

extensively analyzed by Tubadji, Huang and Webber (2021) for containing bias due to the customers' emotion regarding the importance of being human. This is a dataset about customer's evaluation of pieces of music composed by humans or AI. Thus: (i) the unique experimental design of the data collection employed for this dataset and (ii) the existing previous analysis (that has confirmed the presence of the bias of the importance of being human in the dataset) make our dataset an ideal testbed for the ability of the AI algorithms to predict correctly the customers satisfaction. Namely, we aim to test whether the AI can predict correctly the customer's satisfaction with the music once the customer learnt that the composer was an AI. From Tubadji, Huang and Webber (2021) we know exactly how the data is biased, so we challenge the AI to surmount this bias with its precision.

Methodologically, we use two AI algorithms – Lasso and Random Forest. While they are a simple-order machine learning algorithms, they are the ones most widely used by economists. That is particularly helpful to maximize the value added of our results. The added value of our study for the wider audience is that we showcase how AI precision depends on the economic data collection process. As most businesses will not have access to the highest echelons of AI technology, we believe our analysis is therefore relevant to the widest audience. In addition, from an academic perspective, the value added of this study is the Culture Based Development (CBD) conceptual model about the micro-economic mechanism through which culture transforms emotion into an economic order of preferences. This model can be used to collect economically-relevant cultural-bias-free data about customer satisfaction. Such data can next help AI researchers and service owners to produce their own AI for services that can correctly predict customer's satisfaction with AI-delivered services, accounting correctly for the emotional importance of being human.

The structure of this paper is as follows. Section 1 offers an overview of the main topics in the multidisciplinary literature on AI, emotions and services which informs our suggested augmentation of the micro-economic model of human decision making. Section 2 outlines the CBD micro-economic mechanism and lays out its neuroscience-motivation for considering culture as the filter through which emotions get classified as feelings and transformed into preferences in decision making and choice. Section 3 describes the dataset with which we test the ability of the cognitive efficiency of AI to compensate for the inaccuracy in modelling the cultural mechanisms of transformation of emotions into an order of preferences. Section 4 describes the results and offers some discussion of the main implications of our findings, outlining the limitations of the study as well. Section 5 concludes.

1. Literature review

Substitution between humans and AI in services has been mainly considered from the point of view of the ability of AI to substitute the human as a delivering agent. AI is now more efficient than humans in cognitive tasks such as chess playing (Ensmenger 2012; Hassabis 2017). AI algorithms are notoriously good at predicting customer's taste and feeding the right advertisement to the right individuals according to taste (Mogaji, Olaleye and Ukpabi 2020). However, most of AI is diffused in the services provided. If it becomes salient, a key difference between the AI service and the human-frontline service will be the absence of the component of interaction with a human being. According to many recent studies, being human enjoys a special cultural value in the utility function of the consumer (see Carroll et al. 2019; Pelau et al. 2021; Haesevoets et al. 2021; Tubadji, Huang and

Webber 2021). The question this study poses is whether AI is able to account only through its precision for the human behaviour and its positive bias towards being human, which will become paramount if the presence of AI becomes salient in the service sector. To motivate our hypothesis that AI will be challenged to compensate for the inaccuracy of the model that does not account the importance of being human and to understand the motivation behind the omitted mechanism, we offer a multidisciplinary literature overview of the key points of our argument, which stem from the science of developing AI (cognitive science), the sciences of understanding human emotion (psychology and neuroscience) and the science of consumer behaviour and choice (economics). Finally, we explicate the link between the overviewed key notions and the case of AI services in particular.

The purpose of this literature review is to inform and motivate the later proposed CBD micro-economic model. Therefore, we shall outline the main aspects of the contributions from cognitive science and psychology and neuroscience which are currently omitted in economic modelling and that we will use to augment our micro-economic model with in order to add value to the literature on customers' satisfaction and economic choice.

Cognitive Science

Cognitive science is the engine for the development of different forms of AI such as expert system (ES), fuzzy logic (FL), artificial neural network (ANN), genetic algorithm (GA) particle swarm optimization (PSO) and biologically inspired (MI) (see Sutikno, Facta and Markadeh 2011). They each rely on different learning approaches such as deep learning, deep feeling, and various other forms of Neuro Linguistic Processes (NLP) such as emotional recognition in conversation (ERC) (see Pfeifer 1988, Kaiser and Wehrle 1994; Poria et al. 2019). This means that essentially different AI use different mechanisms for learning how to reason and behave similar to observed human behaviour. Human behaviour however is a very complex process with implicit biases entailed. It is therefore very difficult to comprehend this behaviour readily by just observation, and this holds true even for very efficiently observing technologies such as AI. AI development has tried to integrate the observation of human behaviour in different ways – in terms of speech, body gesture, choice and to combine all these pieces of information into reconstructing correctly the behaviour of human agents (see Poria et al. 2019). Two key problems persist: (i) the predictions of human emotions are still far from perfect and, second, what we want to highlight with this article here is that (ii) the response of humans to the success of AI to understand their emotions is little researched. We would like to stress here the first problem in the literature. Namely, the successfulness of AI in understanding human emotions is an outcome that is different from the response of human emotions to an AI addressing their emotional needs instead of another human[2]. The essence of the nature[3] of the supplier is suggested here to be of importance in addition to the characteristics of the service itself. This aspect is still very little researched (Vlačić et al. 2021).

In doing the above explorations, AI developers rely on Cognitive Science, which Pfeifer (1988) explains as the science of making AI that is a concoction of psychology, linguistics, philosophy and neurobiology sciences. We can add that decision trees are clearly

[2] There is most abundant recent evidence on the potential aftermaths of this hypothesis – namely – people seem to behave morally differently when they interact with people and when they interact with AI. For example, Giroux et al. 2022) report that apparently people feel different level of guilt when they interact with machines,
[3] The importance of the essence of the nature of things for human valuation of life is one of the oldest topics in science, as it can be found in philosophical texts such as Spinoza's "Ethics", published in 1677.

part of the methodological set of decision theory and game theory in economics. Notably, all sciences seem to bestow more confidence on the developments in their related fields than of their won and so does Pfieifer (1988). A more careful look at the recent developments in the above listed sciences, elements of Cognitive Science, and their level and approach of engagement with the topic of emotions are offered below to reveal some important caveats in each field and neglected so far complementarities between the different fields.

Essentially, the science of making AI does not have a better conceptual model for predicting human behaviour than economists do. They rely on the observation of the data and empirical work to get the most important customer satisfaction predictions for many industries (Oh et al. 2022). That is why our research question focuses on whether in predictions of customer satisfaction the precision of the AI algorithms can alone suffice to compensate for the bias in the data when the data is collected without accurately accounting for the role of emotion.

Psychology and Neuroscience

Emotions are usually grouped into four to six basic types by psychologists. Some refer to Cicero who used to classify emotions into: fear, pain, lust and pleasure (see Poria et al. 2019). Alternatively, for instance, Panksepp (2007) classifies the basic emotions as: seeking, rage, fear, lust, care, panic and play. The overarching definition for all emotions however is one and it can be summed up as follows. Emotions are instinctive unconscious energies arising in us and setting our behaviour in motion in response to triggers and cues from our experienced reality. How we respond to the trigger is a complex process. Once the unconscious emotion is triggered, it has to be transformed into a cognitively recognized feeling, i.e. to be decoded as meaning for us in a way beneficial for our survival (as for instance in Sutikno, Facta and Markadeh 2011). The decoding and realization of emotion as a feeling obviously contains also a physiological reaction, the synthesis of biochemistry in our body that informs our brain how to perceive the trigger. The physiology of our body has evolved to then respond to the signal chemicals with the release of hormones and enzymes that trigger the evolutionary most beneficial behavioural response to the trigger (see Holt 1989; Bos et al. 2012). For instance, if we encounter a human being, this triggers the emotions of care and fear, we evaluate the degree to which this human is threatening or caring. Next, respectively, we start feeling fear or some degree of altruistic affection to this individual, depending on whether we have perceived them as a source of danger or as a potential protection for our survival (see Mattila and Enz 2002; Lu, Xie, and Zhang 2013).

Our take on this matter in the current study is to highlight the importance of culture in the decoding process of emotions into feelings. It is one's set of cultural norms and heuristics that are used by the individual to shape one's perception of the trigger that stirred their emotion (Schachter and Singer 1962; Khaneman and Tversky 1980; Akerloff and Shiller 2010; Alesina and Giuliano 2015). As we know from philosophy, one and the same trigger from reality can be perceived as either good or bad, depending on the social construction about its characteristics (see Derrida 1967; Tubadji 2020). Put differently, we suggest here that the same triggers of the same emotions will be perceived differently by individuals with a different cultural background and will therefore evoke different feelings in them. This is what is somewhat called cultural relativity in human behaviour (see for example Tubadji, Denney and Webber 2021).

Thus, essentially, neuroscience and psychology have long acknowledged in numerous details that there is emotional side of the mind, besides the cognitive one.

Economics however, even in its most psychologically adapted behavioural economics field, is focused almost entirely on the cognitive bias rather than the emotional aspect of decision making. Thus, our proposed model not only helps AI sciences with providing an accurate model as a benchmark, but also fills a gap in economic science by offering a micro-economic decision making model which is more accurate in accounting for the emotional side besides cognition.

Economics

Economics determines a big part of this how we invest in the development of AI and how we expect (and allow) the use of AI to affect our socio-economic development. Why does economics not account accurately for emotions? Economics started as a moral philosophy science trying to normatively postulate what is the morally and emotionally correct decision-making process (see literature review in Tubadji 2020). The way emotion is termed in the economic theory is in essence "utility", which is a term referring to a somewhat more complex entity, simply explained as the degree of loving something. Gradually, during the 20es and 30es of the 20th century, economics grew convinced that disentangling the moral and emotional aspects of utility is so difficult to handle that it had decided for a long period to dispose emotion and moral altogether from its realm of economic inquiry (see Tubadji 2020 for an extensive overview). This was the period of what is called "value free economics", i.e. a period when the values in the utility function were regarded as an exogenous individually specific fact of life, whose dynamics are the subject of study in other disciplines with incompatible methodological approaches such as philosophy and qualitative psychology. To summarize Tubadji (2020) here, economics focused in this period on studying the clear mechanisms of choice i.e. the behaviour that occurs once people's utility functions have defined the order of preferences of each individual. Put differently, economics started studying behaviour based on the feelings that people have about the options for choice, assuming these feelings are exogenous and non-transitive across options for choice. This is to say, economics suggested that it is reasonable to assume that the same person was supposed to feel the same way about the same options over time and space. With the development of experimental psychology, economics noticed first the experiments with rats (see Scitovsky 1973, 1976; Bianchi 2016) and later on with humans (see Kahneman and Tversky 1980). Economics started recognizing that a multidisciplinary fertilization is possible, as there are behavioural mechanisms that can be elicited with mutual effort. Especially through understanding more about the emotions of fear (in relation to uncertainty) and physical pain and its time-dependent feedback to utility, economics started formally recognizing that the utility of the individual is a complex process with mechanisms of transformation of emotion into feeling that defines the order of preferences (and may as well be different in different periods of time).

Yet, economics knows very little still for most emotions and feelings. Altruism, the feeling related to the emotion of care is a topic for research in game theory nowadays. There are attempts to study this notion not from moral philosophy perspective (see Khalil 2004 for a summary of this stream of literature), but from experimental perspective, establishing the mechanism for the formation of effective altruistic behaviour based on agents' psychological types and economic incentives (see Karlan and Wood 2017; MacAskill 2019; Peters 2019). While the latter game theoretical approach is the current cutting edge research in experimental economics, what is most standard nowadays as an applied economic approach to studying the utility function is the practice of employing what is called a hedonic model, i.e. a modelling approach where individual utility is modelled as a function of a set of economic and social characteristics of an option for choice and the importance of each determinant is established empirically for each individual in the sample (see Ekeland, Heckman and Nesheim 2002). Alternatively, in theoretical economics, agent based modelling or experimental economics relying on game theory, a choice mechanism is assumed or hypothesized and then strictly checked empirically for presence (without any exploration why it is present, while the cultural element is crucial regarding this latter concern).

Utilizing the latter approach in direct or indirect transformation of it, economic and marketing and management studies have generated a small but convincing body of literature nowadays on the utility function of customers from using AI technology (see for example Roberts 2005; Jahn and Kunz 2012; Mattila and Enz 2002; Tremblay et al. 2016; Pelau et al. 2021; Haesevoets et al. 2021). It appears that people do attach a social/cultural value to being human, which is perceived as missing when the same product or service is produced or delivered by an AI agent rather than a human front-liner. Examples sprawl from health services, to financial services, to management systems and replacing different management levels with AI (see Grove, Kar and Dwivedi 2020; Payne, Dahl and Peltier 2021). Across industries and hierarchies of tasks performed within the economic enterprise, the importance of being human was always consistently documented as part of the utility function of the consumer.

Thus, essentially, we contribute an original hypothesis to the enormous body of literature on utility and preferences in economics. Our original proposition here is that emotion is evaluated and coded as a good or a bad feeling according to a filter of historical evolutionary memory in the form of cultural heuristics, partially endogenous to individual experiences. Thus, the emotion, coded into a good/bad feeling, informs the order of preferences for the triggers from the surrounding environment. This decision making culturally determines which triggers will be responded worst, worse, better and which best by the decision maker. The emotion related to the importance of being human (as part of customers satisfaction and choice) is one example of the application of this cultural economics mechanism.

The case of AI Services

The above suggested augmentation of the economic model based on neuroscience and psychology is particularly important in the context of services. And it is particularly so in the context of the servitization of the economy (Kowalkowski, et al. 2017), coupled with the new technological revolution and the spread of AI technology (Vlačić et al. 2021). The reasons are outlined below.

Research on emotion and AI services has highlighted one very important aspect, uniquely noticed in this field of research and crucial to understanding better the above summarized literature. Namely, studies of AI services have synthesized and provided very filigree and nuanced evidence on the importance of the dyadic interaction between the human front-liner and the customer for the emotional channel in customer's behaviour (see Zablah et al. 2017; Lin, Chi and Gremler 2019).

This has been achieved in particular by the literature on disrupted service provision and the emotional channel in customer satisfaction upon service recovery. This analytical setting is particularly suitable for analyzing emotions and behaviour, since the disruption of the service provision is a trigger of unsettling emotions with observed consequential behaviour in terms of responding, handling and eventually reengaging cooperatively with the service provider. In this process, the emotional engagement of people as customers and front-line service providers has been studied in great detail. It appears for instance that the ethnic proximity reveals social pleasing biases. And in the same time, the success of emotional connection between the customer and the front liner has a crucial role for the outcome of the service recovery for the company (Boshoff 2012).

Importantly, this literature has also elicited the types of intelligence that AI should develop in order to be able to adequately satisfy the emotional channel in customer satisfaction. There are varying taxonomies and classifications. Huang and Rust (2018) propose mathematical, analytical, intuitive and empathic types of intelligence. Alternatively, Huang and Rust (2021) simplify those to mechanical intelligence, thinking intelligence and feeling intelligence. While there are good theoretical and practical reasons (vis a vis the research question analyzed by the authors), we would like to draw the attention here to yet another question. Even when AI develops all these types of intelligence and becomes able to understand and respond to the emotional aspect in the behaviour of humans, we still need to explore what the response of humans to interaction with AI rather than with a human might be. Research on human services has some further insights on this too, stemming from what it has learned about the mechanisms of dyadic human to human interaction in business to client types of settings (Zablah et al. 2017). Important rare attempts in using this existing knowledge are present in the form of the emerging AI device use acceptance (AIDUA) studies as part of the AI servitization stream of literature (see for example Gursoy et al. 2019; Payne, Dahl and Peltier 2021). There are also other independent contributions showing that people have strong emotion related to human delivery of services in managerial decision making (Haesevoets et al. 2021) and virtually in any other field of human activity – health, education, commerce (see a comprehensive literature review in (Pelau et al. 2021). Based on this, we summarize below three important missing components in the attempt to explore the emotional response of customers to AI services as economic substitutes for human services.

First, emotion depends on culture. Insights relevant to this still missing link have been documented by many (such as Boshoff 2012) that demonstrate that cultural and ethnic proximity matters in the type of response to the same trigger from reality. It was also documented that a complexity exists in the customer emotional response to the service interruption or failure depending on whom they are venting and sharing their emotional response to. The opportunity of dialogue with the general public (strangers) seems to have a most significant positive effect, because of the particularities of the situation. While communication with close to us individuals is generally more emotionally rewording, in case of services dissatisfaction the function of communication with others is targeted at maximizing our cultural impact on the trust that the society has towards the institution that we have perceived as harming our interests by interrupting its service (see López-López, Ruiz-de-Maya and Warlop 2014). We interpret these important results as follows. Engaging with strangers rather than close individuals brings clearly more satisfaction to emotionally disrupted clients because it helps them to achieve the cultural outreach outcome more efficiently in terms of spreading the information about trustworthiness wider than their immediate social circle.

Second, culture is fundamental building block of trust, and this is well known in economics (Tubadji 2021). However, how does this affect the impact of emotion on choice? DeWitt, Nguyen and Marshall (2008) demonstrate the paramount role of trust in establishing the link between customers emotions and the construction of customer loyalty in human to human type of service provision. Trust has been documented as very sensitive and important element of behaviour in self-driving car research (Raue et al. 2019). Music generation (AI generated electronic music) ultimately is subjected to intentionally being corrupted post-factum of its AI-generation to become closer to human performance and thus appeal more to the consumers (Hennig 2014). The exact development of trust in AI services is somewhat less researched.

Further, Schoefer and Diamantopoulos (2008) have revealed that the role of emotions translating into response to recovery of service provision is strongly dependent on perceptions of injustice with regard to the experienced service failure. Their model suggests that perceived injustice drives importantly post-complaint behaviour after service recovery.

Thus, culture, trust and perceptions all seem to have a role as a joint mechanism transforming emotion into feelings and order of preferences ruling over customer's choice and action. But this mechanism is a missing or partially included component in the way that most of the literature on AI services treats the utility of the consumer. Meanwhile, this mechanism seems to have an impressive body of literature documenting its relevance. Clearly, understanding better the operation of this three-step cultural micro-mechanism of transforming emotions to preferences has important implications for AI service providers.

2. A CBD Micro Model for Culture, Emotion and Customer's Choice

Culture Based Development (CBD) is a methodological paradigm that puts cultural bias in the centre of studying economic choice on micro and macro level (Tubadji 2012, 2013). CBD suggests that formal cultural norms and informal cultural heuristics serve as a psychological defence from pain due to anxiety in front of uncertainty (see Tubadji 2021).

We suggest here the CBD inspired proposition that culture can be thought of as the collective memory of trustworthiness of the triggers from our surroundings. Therefore, cultural bias is particularly emotionally important in the utility function of people from an evolutionary perspective. As we know from Prospect Theory, prospects of pain amplify the absolute size of utility, leading to an emotional response to adversity with double the size of the response to the same trigger under favourable prospects. For instance, negative change of income with 10% as a trigger is twice more likely to prompt behavioural response of withdrawal than is eagerness to adopt proactive behaviour likely to occur in response to the same trigger but with positive prospect to win the 10% of income. This is known as 'loss aversion' (Kahneman and Tversky 1980; Schmidt, and Zank 2005). In addition to this size effect, and in line with CBD and the constructionism and deconstructionism schools in philosophy (see Tubadji 2020), we suggest here that the qualitative evaluation of prospects as adverse or favourable is culturally defined.

A particular case regarding the emotion towards AI services that CBD has elicited is that customer's emotions and utility functions are sensitive to the importance of being human in a complex but analytically clearly detectable way. Namely, Tubadji, Huang and Webber (2021) show that the same sample of music is downgraded in ranking by the consumer upon getting informed that the composer is an AI rather than a human being. Tubadji, Denney and Webber (2021) show further that the cultural context moderates the customers' response to AI and robo-advisory in the banking sector.

Based on this, we would like to suggest here a general CBD micro-economic model of transformation of emotion into feeling and order of preferences. This model builds on the premise that the CBD mechanism depicts a cultural filtering of emotions through perceptions thus creating meaningful feelings for the decision maker towards the particular trigger as an option for choice to act upon. The conceptual side of the CBD model, its operationalization and application for testing the working hypothesis of our study (focused on the example of customer satisfaction) shall be explained below.

Figure 1 provides a synthesis of the CBD interpretation of the multidisciplinary literature on emotion, culture and feelings, linking these three components into a joint mechanism generating order of preferences. It tracks how emotions are culturally filtered based on trust into perceptions that are crucial for the formation of feelings and their transformation into preferences for choice.

+++ Insert Figure 1 about here +++

The CBD model in Figure 1 suggests that in order for a behavioural choice over the mode of responding to an emotional trigger to be made by the customer, emotions need to be decoded by culture into: (i) good or bad; (ii) a degree of good or bad.

The first aspect of the cultural filtering mechanism is explained by cultural constructionism (Derrida 1967)[4] and defines the sign (positive or negative, i.e. good or bad) of the feeling based on the cultural perception. The emotions based on triggers culturally perceived as positive triggers transform into positive feelings; and emotions evoked by triggers culturally coded as negative triggers transform into negative feelings.

The second aspect of the cultural filtering mechanism is responsible for the formation of the magnitude of the feeling and relates to culture and order of preferences as follows. Culture codes the emotion into more (closer to absolute value of 1) or less (closer to 0) trust-worthy with regard to affecting our reality indeed. This classification then determines the ordering of the preference for responding stronger to the trigger when the trigger is less trustworthy. This is a culturally driven response to the notion of trustworthiness. Namely, the formation of perceptions of likelihood of the event determine the strength of the feeling it evokes. Events perceived as more likely evoking a stronger feeling. The stronger the feeling, the higher order of preference it generates for its trigger if the latter is an option for choice among other options. This second part of the cultural filter is the main original conceptual contribution of our study[5].

[4] An interesting suggestion by Akerloff and Rayo (2020) lately proposed in narrative economics is that a cultural evolutionary narrative of what is pure and clean (and therefore favourable of survival) is how culture filters the emotional triggers and makes meaning about them and shapes the good or bad feelings towards them. This reasoning is in line with Panksepp (2007) and Panksepp and Watt (2011) claiming that disgust is a basic emotion. A basic emotion is defined as the ability of a physical (brain) response to triggers with essential consequences and aftermaths for survival (Panksepp and Watt 2011). We argue here that this all narrows down to a more general memory of trustworthiness of the trigger as resulting in bad or good survival aftermaths for the ancestors of the individual. The heuristic records whether the trigger is observed to be bad or good for survival and thus the trigger is coded as a good or bad trigger in the heuristics of the local cultural from which the observations are pooled. Thus, we argue here that culture operates as an information filter crucial for the navigation of basic emotions. This cultural filter uses the imprint of the collective memory of experiences with the reality and interacts it with the biological memory of the species in the individual. That is why culture is deeply cherished by every individual due to an instinctive survival instinct. Importantly, we argue that what these basic emotions are felt towards as triggers is determined based on the cultural heuristic memory of what consequences each trigger has caused in the past. So, the cultural coding of triggers as good and bad is culture and place and time specific (as opposed to universal).

[5] The here proposed CBD mechanism of cultural trustworthiness coding of perceptions is compatible with the game theoretical handling of the accumulation of trust in continued cooperation (Croson and Buchan 1999; Johnson et al. 2011; Alós-Ferrer and Farolfi 2019). However, CBD suggests that culture stores the past experiences of our community and forms them into heuristics what is likely or not likely and that is how this memory gets preserved to tap on by individuals who have not yet experienced the trigger to have their own

Economic theory suggests that the decoding of emotions into feelings and their transformation into preferences is a relatively stable process which leads to non-transitive ranking of preferences and options for choice. That is in essence the condition under which people are assumed to be rational. CBD agrees with this assumption in a weaker form of it. The stability of the order of preferences is present only as long as the degree of cultural bias on choice remains constant. If a person gets exposed to a new cultural milieu which holds a different set of heuristics of what is to be coded as good or bad triggers, the person may experience a change in one's preferences (see for example Sam 1995). Even when remaining embedded in the same culture, if a person gets exposed to personal experiences with a certain trigger that differ qualitatively from the local cultural heuristics coding of this trigger, or has a frequency different than the cultural heuristics expects, this can reshape one's cultural beliefs of trustworthiness in the trigger as good or bad. This will redefine their preferences in a similar way as in repeated games the breach of trust does (see for example Yu et al. 2014)[6].

Economic game theory and many other sources have demonstrated the role of trust in human behaviour over time and so do related disciplines (see Lunawat 2013). Grove, Kar and Dwivedi (1991) show that trust determines 37% of the clients' satisfaction with AI. Trust is shown to matter on micro and macro level (in the sense of social capital) for the use of AI and robo-advisory in the financial sector (Tubadji, Denney and Webber 2021). But trust is a very complex entity. People seem to value being human so much, that it is known that they would rather not trust car GPS that does not make mistake than one with more human-like error propensity and their trust is also further biased by the culturally defined reference group of the user (Hsu and Lin 2010). Furthermore, paradoxically, while people report unwillingness to obey AI bosses, de facto when put in the position to interact with an AI boss, about half of the people (46%) actually do obey the orders received (Huang and Rust 2018). And people were prone about 70% to prefer human-based advice (rather than AI one) in managerial decision making (Haesevoets et al. 2021). Thus, the relationship of trust with the formation of perceptions, feelings and ultimate choice and behaviour is a complex process.

In addition, under exogenous shocks, such as the disruption of a service and service failure, for example, the latter triggers emotions of fear and the customer experiences increase of uncertainty about the classification of a certain option for choice as perceivably trustworthy (see for example Gabbott, Tsarenko and Mok 2011; Duan, Edwards and Dwivedi 2019; Singh et al. 2019). The perception under increased uncertainty is, as we know from Prospect Theory (Kahnemand and Tversky 1980), acting as a multiplier for the negative feelings of the person who experiences uncertainty. This amplifier tends to generally double the negative feelings. Moreover, what we know from the literature is that when trust is high, uncertainty is low and vice-versa (Fjaeran and Aven 2021). Thus, CBD accomodates in its model the rationale that if trust decreases during interaction, this will trigger uncertainty and double the negative feeling and lead to lower ordering of the trigger in the preferences for choice by the customer.

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memory of trust in a continuous game. This is an original CBD application of the idea of heuristics from prospect theory (Kahneman and Tversky 1980) with crucial importance for the cultural filtering in the formation of ordering of preferences.

[6] Clearly, there are also economic endogeneities in the shaping of attitudes as well known in the economic literature – we know that various economic incentives and times of economic shocks can influence attitudes (see Wilkes 2008, 2011; Turner and Cross 2015; van Heerden, and Ruedin 2019; Grigorieff et al. 2020). Yet, these are outside of the cultural filtering mechanism which is the focus of this study.

Why the here proposed CBD model is particularly relevant for the case of services as an example of its application? Building on psychology, we can state that one of the basic evolutionary important emotions is care and it requires a dyadic in nature behavioural interaction with another human being. The CBD model adopts the stand that this caring emotion is what transforms into altruistic feelings, love of social interaction and love per se. In other words, the emotion of care is evolutionary related with being related with other humans. Therefore, creating cultural heuristics to guide their own behaviour, people have evolved into developing the cultural valuation of being human, i.e. a socially constructed perception of value that is strongly embedded in the survival mechanisms of our behaviour. Thus, replacing the human service provider with an AI results into a condition of decreased trust. As the provider is simply not human, this is perceived by our cognitive system as an evolutionary threat to satisfying our caring emotions.

This CBD model and its analytical logic can be applied in particular to understanding the emotion of the AI service customers. These customers and their feeling of satisfaction with the same quality of AI service as a substitute of a human-based service can be expected to be sensitive to the factor of being human that is lost in the substitution process.

The CBD micro-economic model and its application in the substitution between AI and human-based services relies on clear economic fundamentals of the indifference curve as follows. As long as the AI and human service are not perfect substitutes by nature of the provider (human and AI), the indifference curve is convex. Therefore, the availability of more AI and less human-interaction will be associated with a marginal rate of substitution and a movement along the indifference curve corresponding to a higher level of valuation of the human-based service when there is less of it and lower valuation of the AI service of which there is more. Again, following the convexity characteristics of the indifference curve, this effect will be further intensified the more AI is available to the client and the less human interaction is available to this same client. Figure 2 below illustrates this reasoning.

+++ Insert Figure 2 about here +++

Our empirical quest in this paper is whether an AI machine learning algorithm can compensate and form correct predictions (through its efficiency of learning from human behaviour observation) without explicitly modelling the CBD mechanism with regard to the importance of being human in its AI model. If the AI precision can compensate for the cultural element, then the latter is just a bias. If however the AI precision cannot correct successfully for the omission of the cultural valuation of being human, then the latter is an important component of the utility function of the customer.

To test this, we shall obtain the AI model predictions of human satisfaction with the service based on observed human behaviour towards this service when delivered by a human and compare these predictions to the self-reported actual customer satisfaction with the very same service under AI provision. Thus, the empirical aim of our study can be summarized as the objective to test the general CBD hypothesis that:

H01: AI cannot compensate with its machine learning efficiency for the lack of an accurate model for the cultural mechanism of transformation of emotion into preferences and choice.

3. AI Ability to Predict Customer's Choice under the Omission of the Cultural Valuation of Being Human

Data

This research uses a unique dataset, which was collected through an experimental design: people were asked to evaluate their satisfaction with four piece of music and then were informed that two of them were composed by an AI and were asked to re-evaluate the pieces of music after receiving the information about their composer. This experimental design is crucial in helping to clearly identify the "importance of being human" as the treatment effect that drives the difference between the initial evaluation of a piece of music and its re-evaluation by the same customer upon the release of information that certain pieces of music they evaluated were AI-generated and not composed by humans.

This data-generation process offers two outcome variables about human satisfaction with the service – the first one is based on customer's pre-information evaluation of the piece of music that does not reflect the CBD mechanism of emotion, culture and choice. The other carries the true evaluation (i.e. the one triggered by the revealed nature of the composer) accounting for the importance of being human in the customer's utility function.

This data was previously carefully analyzed by Tubadji, Huang and Webber (2021) and they established through series of econometric tests that indeed people downgraded the music once they learned that it is composed by an AI and pushed up their evaluations of the music that they realized was composed by humans. Put differently, we know that the pre-evaluation data carries a bias due to not accounting for the customer's emotion about the importance of being human and OLS is biased in estimating it correctly. The current paper aims instead to test whether the precision of the AI algorithms, such as Lasso and Random Forest, can help the AI prediction to come closer than an OLS to correctly predicting the re-evaluation of the AI-generated music by observing the data that does not reflect the CBD model for emotion, culture and choice.

In particular, the data used in this study is obtained from an experimental online survey collected within 3 days within starting on 30th March 2019. During this time, 974 respondents evaluated the quality of 4 music samples, thus amassing 3808 observations of customer satisfaction. The survey offered four samples of music (used here as a proxy for a creative service) – sample 1 and 3 were human generated and samples 2 and 4 were AI-generated music. The experimental element of the survey entailed asking the participant to rank their evaluation of the music samples according to the five main objective criteria for music quality according to musical theory (melody, harmony, rhythm, coherence, overall impression) without knowing the nature of the composer and then re-inviting the participant to re-evaluate these same 4 pieces of music after being informed that sample 2 and sample 4 are AI-generated. As pointed above, previous research by Tubadji, Huang and Webber (2021)uses this dataset and shows that the changes between the first and second round of evaluation varies significantly not due to the pre-evaluation-known customers' observable characteristics but due to the triggered emotion of the customers regarding the importance of being human. In this study, we will focus on using the AI-generated samples 2 and 4. This is motivated by the nature of our research question, which is interested in the predictive evaluation of customer satisfaction with the quality of an AI-delivered service.

Besides the subjective hedonic music evaluation information measured on a 1-10 Likert scale, we have available collected demographic characteristics (such as age, gender, income) and information about the musical tastes, musical education, relatives with musical background and objective evaluation of the music according to the main 5 criterion of musical quality (see Appendix 1 for the full list of variables and their descriptive statistics).

Figure 3 and Figure 4 present respectively the descriptive statistics about the distribution and the correlation between the hedonic evaluations before and after the treatment (in the form of information about the AI-nature of the composer) was released. As seen from the two figures, there is certain relationship between the pre and post evaluation, but there is also noticeable violin plot dissimilarities and considerable deviation on both sides of the fitted line between the two rounds of evaluation. Therefore, it is a valid research question whether the AI algorithms with their enhanced efficiency in prediction of human behaviour can manage to overcome the omission of the information about the cultural valuation of being human. Hence, this study asks whether an AI algorithm can shape correct predictions for the valuation of AI services (only through observing the usual customer behaviour and preferences towards human-provided services), or not.

+++ Insert Figure 3 & 4 about here +++.

Furthermore, according to Boehmke and Greenwell (2020): "The sample size parameter determines how many observations are drawn for the training of each tree. Decreasing the sample size leads to more diverse trees and thereby lower between-tree correlation, which can have a positive effect on the prediction accuracy". Thus, our dataset and its sample size of around 3000 observations should be giving the best chance for the AI algorithms used to come the closest possible to the accurate predictions. Our research question in this study is whether the AI algorithms will actually predict the customer satisfaction any closer than an OLS without accounting for the CBD mechanism of emotion, culture and choice that we know present is a bias in the dataset.

In a nutshell, the major advantage of our dataset here is that we know the process of data generation behind it thanks to Tubadji, Huang and Webber (2020). We know exactly what biases are present in the behaviour of the individuals due to the information about the nature of the composer that generated the differences in the re-evaluation of the music. We know that only a careful modelling of the difference in differences can identify this bias in an OLS setting. We aim to empirically establish here whether an AI-prediction of the re-evaluation of the music can be precisely predicted by the AI algorithms based only on the biased data with no use of the CBD model to correct for the bias.

Method

In order to test our hypothesis H01, we adopt the hedonic valuation model used in Tubadji, Huang and Webber (2021) to explain the emotional satisfaction of the customer with the sample of music. This model contains 19 explanatory variables, grouped accordingly into demographics and objective music quality valuation. We assume that such a hedonic model is the one a standard AI-based service providing machine will use in order to learn whether it is satisfying the customer.

According to our CBD model suggested in this study, H01 can be expressed as follows:

$$True\_AIservice\_valuation = f(Pre\text{-}Experiment\_hedonic\_model;\ Value\_Being\_Human) \quad (1)$$

In other words, model (1) shows that the true post-experiment re-evaluation of the music (after the information treatment about the AI nature of the composer is provided) is a function of the vector of determinants of the initial hedonic valuation model (or its outcome variable) and the cultural valuation of being human. This cultural valuation is a product of the cultural truth filter, the corresponding coding of the service as less trustworthy because delivered by an agent of a non-human nature (who is culturally more distant and hence feels less trustworthy for a care-needing human being). This formed less-favourable perception distorts (and as we know from Tubadji, Huang and Webber 2021) actually decreases the valuation of the music once the AI nature of the composer is revealed. This can be reinterpreted as meaning that when an identical quality of service is delivered by an AI rather than a human front-liner, the customer is likely to have the propensity to factor in their evaluation of the service not only all the usual quality assessment factors but also the lack of the cultural value of being human. The latter factor may as well vary across individuals but H01 suggests that it is a significant factor for predicting human behaviour per se and not just a source of precision bias on choice.

If the value of being human is just a non-significant disturbance for learning the *True_AIservice_valuation* by the customer, then a more precise and efficient algorithm with AI nature will be able to predict the *True_AIservice_valuation* based on the information from the pre-experimental_hedonic_model only. If however the AI algorithm predicts more poorly the *True_AIservice_valuation* than the *Pre-Experiment_hedonic_model,* then this will mean that our hypothesized cultural *Value_Being_Human* is indeed an important factor whose omission from the model causes underspecifcation of the model and leads to worse general fit and worse predictive power of the AI-algorithm model for understanding the satisfaction of the customer.

Technically, to test our hypothesis, we implement a Lasso adaptive estimation and compare the pre and post estimation of the best fit lasso model (according to CV and EBIC criteria, and we shall present only the latter for brevity). We do this procedure for the pre and post-experiment valuations of the music, explaining them according to the Tubadji, Huang and Webber (2021) hedonic valuation model with 19 variables. Next, we compare the goodness of fit of the best lasso model for the pre- and post-experiment valuation with the predictions of pre-info-treatment hedonic valuation. If there is a decrease of the goodness of fit in the case of the post-experiment predictions of the lasso algorithm (Zou 2006), we consider this is a sign that our H01 cannot be failed and the cultural valuation of being human plays an important role in the utility function of customers.

To implement a within method triangulation and a kind of a robustness check, we implement a Random Forest algorithm for classifying and predicting the valuation of the music in the pre- and post-experimental round of evaluation. We compare the out of the bag (OBB) error of the models. If the OOB error is bigger in the post-experimental sample, this means that the cultural valuation of being human is a component which even a more powerful AI algorithm with higher efficiency cannot compensate for as an omission in the model (see Breiman 2001; Matthew 2011).

We implemented many variations of the lasso and random forest estimations which are available upon request. The findings are consistent with the basic results selected to be presented below for brevity.

Results

Table 1 presents our results from using the Lasso procedure for learning the true satisfaction that the customer will derive from the service (approximated with the sample of music). The table shows 8 specifications. The first four regard the valuation of music sample 2 and the last four specifications regard music sample 4. The first specification for each sample of music is estimated via the standard OLS regression, which is comparable with Lasso adaptive estimations for technical statistical reasons (see Zou 2006). The Lasso specifications for each sample of music present the pre and post coefficients according to the best fitted by Lasso model for customer satisfaction regarding the same outcome variable as in the preceding OLS estimation. This reporting is repeated for the pre and post treatment valuation for both sample 2 and sample 4.

+++ Insert Table 1 about here +++

As seen from the results in Table 1, the lasso-based R-squared regarding the post-experiment re-evaluated samples is always performing worse than in the case of the pre-experiment standard hedonic valuation of the same identical service with not much substantial difference from the simple OLS. The AI algorithms are also choosing more parsimonious models than the standard OLS, but these have inconsistent composition of the utility function identified, while the object of evaluation is always a sample of music generated by AI. We interpret these findings in the sense that the AI algorithm is less able to predict actual AI-service customer satisfaction if trying to learn about customer satisfaction from human-service customer satisfaction data.

Table 2 presents our results from employing the Random Forest algorithm to learn the true valuation of the AI-generated product/service. These results are a form of robustness check for the findings in Table 1 and are indeed consistent with the above described findings.

+++ Insert Table 2 about here +++

As seen from Table 2, the OBB error is clearly higher when the determinants of the pre-experiment model (without awareness that the music is generated by AI) are used to the predict the satisfaction with this identical service if its nature is perceived as based on an AI-provision. The AI predictive power for customer satisfaction with regard to the same music but under the condition that people perceive it as an AI piece of music is as poor as standard OLS, in spite of the technically higher precision of AI predictions. For sample 1 the defective difference in AI prediction amounts to 0.015 higher OBB error, while for sample 4 it amounts to 0.024. These findings are clearly consistent with our reported findings regarding H01 above. AI seem unable to compensate through its precision for evaluating correctly the utility for AI-services when not accounting for the valuation of being human as a significant predictor of the utility of the customer.

Discussion

Our CBD model suggests that the reasons for the observed lower efficiency of AI algorithms in predicting the actual satisfaction with the same service, when it is perceived as an AI generated service, is the misspecification of the model with regard to the utility function of the customer. The true latter function includes the determinant of the cultural value attached to being human, which is equally satisfied across all observations in a human to human business-to-customer dataset. This factor of the nature of the interaction (human or non-human) is a self-standing factor for customer's utility, substantially different from the aspect whether the interaction process was a successful communication or not, and refers rather to the nature of the interaction as a human exchange which addresses a basic evolutionary established cultural valuation of the emotions of care and fear which are traditionally satisfied through human history by the presence of other human beings.

In essence, what we find is expected statistically speaking and confirms that the cultural valuation of being human is an important true component of the utility function of the customer. If an important determinant is omitted from a model, then we observe what is termed an under-specification of this model and the results obtained with this model are biased. This reflects in worse goodness of fit and lower predictive power of the underspecified model in comparison to the fully (correctly) specified one.

Therefore, finding that a prediction of customer satisfaction is less successfully predicted by the standard hedonic model determinants when we introduce the information for the composer being AI is a signal that the latter is a significant determinant in this model. This reconfirms that the cultural valuation of being human is an important component of the utility function of the customer, in line with the findings in Tubadji, Huang and Webber (2021).

The finding that the cultural valuation of being human, in its nature of a cultural factor, leads to under-specification of the economic hedonic valuation model of the utility function is a finding that is also consistent with the more general CBD claim that every economic model is under-specified if it does not account for the cultural factor (see Tubadji 2014).

Moreover, our results show that just observing customer behaviour cannot easily predict the changes in customer behaviour under exogenous shocks such as the new information provided experimentally in the survey. Our findings show that apparently, AI-related increases in efficiency of the precision of prediction are not sufficient to overcome model inaccuracy.

Beyond the CBD conceptual consistency of our results, the presented findings, in their economic meaning, are particularly consistent with the findings by Pelau et al. (2021) who report that objective antropomorphism does not affect client satisfaction as successfully as the emotional aspects of empathy. This is in line with the fact that the characteristic of the service itself cannot be expected to predict the satisfaction when degrees of human interaction are lost from the experience (implicitly implied by the fact that the composer of the music is not human). Similarly, our results are in line with Hsu and Lin (2010) earlier finding that actually people were more satisfied with the car GPS not when its objective characteristics were maximized in accuracy, but when the GPS was optimally close in human propensity to make an error.

From statistical point of view, our findings are in line with Mueller (2020) who maintains that many Random Forest models only very slightly improve the OLS with fixed effects predictions (which he illustrates with data for attendance at baseball matches). The findings we present are also consistent with the reported marginal differences between OLS and Random Forest in foresting, offered by Cosenza, et al. (2021). The latter study however offers some words of hope that more advance AI methods such as k-nearest neighbours (kNN) might have better success than Random Forest. Yet, practically, this leads to the same implications from our findings, as it is very likely that most businesses will not be able to afford the use of the most advanced AI predictive tools and will thus risk overoptimistic expectations about their customer satisfaction. It is also possible that the stronger kNN might actually lead to an even augmented error of the bias generated by the 'importance of being human' (Raisch and Krakowski 2021). This is a matter of empirical exploration in future studies.

Implications

Learning more about the reasons for the failure of AI algorithms to predict human satisfaction with AI-based service based on mere observation of customers consumption of human based services can be useful in two ways. It can be used both in the development of AI machines that optimize service satisfaction and also in business analytics that try to predict customer satisfaction with AI services using observations of people consuming human services. Our dataset is designed in such a way that it allows a clear identification of the "importance of being human" as the source of the bias that is present in the re-evaluated data. So, we can offer a well-informed depiction of the inability of AI algorithms to predict the satisfaction of the client with the service using their consumption information before the bias was intentionally corrected by the experimental design in the data generation process. Below we develop the implications from the point of view of the supply (AI services), demand (consumer of AI services) and the entire market perspective, thus covering all economic dimensions that the CBD micro-economic model can help to address.

From the perspective of the provision of AI services, the main direct and specific implication of our findings is that providers of services cannot rely to seamlessly substitute the human frontline with AI provision of services. If customer satisfaction is to be preserved at current levels and not to allow it to deteriorate, human in the loop will be necessary even if AI are developed up to the level of understanding and technically reciprocating fully human feelings. The reason for this is the fact that services include two components – the objective characteristics of the service and the surrogate (externality) effect of offering a field of human interaction. The latter is sometimes holding a threat as interaction may be inefficient even between humans (see Lin, Chi and Gremler 2019) but the very presence of this interaction serves another essential need for the customer – the basic need for human communication that satisfies the basic caring emotions. Our CBD model implies that this need (to satisfy the importance of being human in a service interaction) is potentially the explanation for the often-observed aggression against AI services, especially in generally peaceful but very social-interaction-norms intensive societies such as Japan. The lack of human social interaction is likely perceived as unjust behaviour – a condition justifying anger transforming to an aggressive response. This interpretation is related to the existing in the literature evidence that the effect of perception of unjust treatment in services leads to aggression in human to human interaction settings (see Schoefer and Diamantopoulos 2008; Lu, Xie, and Zhang 2013).

Regarding the demand side and the consumer, our findings imply that humans value "being a human" to an important extent in their utility function that drives their choices. This is of course consistent with the notions of the human as a social animal and more specifically of effective altruism (MacAskill 2019; Peters 2019), which is a form of altruism not driven by cost benefit but by emotion and type of personality maximizing the overall good to the human system. The CBD take here is that this feeling is based on the emotion of care which requires the presence of another individual be it as recipient or source of care. Therefore, the presence of another human has an unsubstitutable value in the utility function of a human being as it addresses the need of a basic emotion. We can speculate that other living beings such as pets or even wild animals have been used as partial substitutes and this is likely to be due to their ability to reciprocate with care as living beings. However, it can be argued that the substitution is never deemed perfect. And the same is likely to apply for developed AI versions that may reciprocate. The AI are likely to still rank less than humans simply because their emotion and reciprocation is perceived as fake since it is designed and pre-programmed by an outside decision process and not independently (freely) chosen by a living and feeling individual as a genuine caring attitude towards the human interacting with them. In a sense, AI can be emotionally perceived as much as polite but not as caring and kind, because the latter two assume intentional living individual as an agent.

Ultimately, from the perspective of the entire economy, this general take from our analysis means that businesses are likely to lose customer satisfaction every time where a human frontline interaction is now present. If the loss of human interaction is partially unsubstitutable in the utility function, as we argue in this study, then there will always remain a small part in the customer satisfaction lost even when AI are of higher sentimental ability than their current versions are, due to the clear perception of the customer that the agent is non-human. Diffused AI presence or secluded one is of course not ethical from legal point of view as the customer is entitled to know the nature of what is provided to them (see Noah 1994). Thus, a loss of satisfaction under fair (information-wise) treatment of customers is inevitable. Indifferent how small the change in customer satisfaction might be due to the loss of the joy of interacting with a human provider of the service, as we know from complexity theory, very small changes can produce very significant impact on the entire system (see for instance Siegloch et al. 2016).

Finally, these implications are likely to affect not only the economic process of the system, due to customer dissatisfaction, but also the mental health of the customer and social wellbeing. If the customer's opportunities to satisfy human interaction and care on daily basis are reduced across all their everyday activities due to the over-digitization of services in the entire world of their environment, as previously shown in Figure 2, this will likely affect detrimentally the mental health of the customer (see Tubadji 2021). The here strongly suggested presence of such negative externalities (due to decreased frequency of human interaction experiences) to the development of people and places needs to be carefully consider. That's particularly important to raise as a red flag in the context of the euphoria with the transition to a new technological era and the increased economic efficiency gained by the substitution of humans with AI technology.

Limitations

A first notable limitation of our study is the fact that there are alternative powerful machine learning algorithms, other than lasso and random forest, such as gradient boosting, support vector machine (SVM) for example. These alternative algorithms could be also tested for their ability to overcome the omission of the cultural valuation of being human from the estimation model. It is possible that they are more efficient in learning the true human behaviour to AI service-providers based on the observation of customer satisfaction with the same service provided by human front-liners.

However, as highlighted in the discussion section, it is also true that the introduction of AI algorithms in services is not likely to always be implemented with highest order AI algorithms (Al Ridhawi et al. 2020). Therefore, our findings demonstrate that using less developed AI algorithms to predict human satisfaction with AI services can certainly result to misleading expectations about the customer satisfaction with the AI service even if the AI service quality is objectively identical to this same service when delivered by a human.

It is also important to note that while our treatment is clearly identified due to the experimental nature of our data, we need further data in order to quantify the three elements (culture of trust, perception and feeling) that the CBD model suggest as operating behind the cultural valuation of being human. Put differently, while we convincingly capture the presence of the CBD mechanism behind the cultural valuation of being human inside the utility function of the customer, it remains for further research with more data availability to test the inside mechanics of this CBD mechanism suggested here. Again, for further research remains the exploration of the cultural relativity of the valuation of being human with regard to the AI-human substitution effect. The availability of ethnic information in an experimental dataset like ours could allow for such further explorations.

4. Conclusion

The current study offers an insight to a neglected, but well founded in multidisciplinary research and evidence, bottleneck in the substitution of humans with AI, especially in the service sector. This bottleneck is the fact that the collective effort is focused on ensuring AI can deliver identical service as a human, while little is done in attempting to explore whether customers would perceive and value the technically identically delivered AI service as a perfect substitute for its human-based alternative. We propose that the reason for this to be an important bottleneck is the cultural valuation of the importance of being human. The latter is a significant part of the utility function of customers that cannot be perfectly substituted by AI.

To motivate this proposition, we offer the CBD micro-economic mechanism based on emotion – perception – feeling. This mechanisms serves for the transformation of basic emotions (such as care) into perceptions for the degree of satisfaction (or intensity/magnitude of this emotion) associated with a given trigger; thus, emotions transformed into a cognitively and culturally shaped feeling as to whether this option is desirable and to what corresponding degree it is desirable in comparison to alternative options. This feeling serves to inform the ranking of preferences of the individual. Based on this conceptual model, a hypothesis is stated that AI services fail to pass the emotion-perception-feeling filter equally successfully (i.e. fully substitutably) as human front-line service providers do, since people perceive AI as qualitatively different from human beings by nature and therefore a need for human interaction in services remains clearly unsatisfied. This also presumes that no matter how high the technical quality of the service will be in mimicking a human service, or even exceeding it, the nature of the service as AI-based rather than human-delivered service will always remain.

To test this hypothesis, we use a primary dataset of over 3000 observations collected online through an experimental survey. The experiment entails inviting the participants to evaluate the same piece of creative service (music provision) once before knowing that it is AI-generated and afterwards being supplied with this piece of information. If the importance of being human is not significant in the utility function of the individual, omitting it in the prediction model will not generate substantial biases, especially if the prediction for customer satisfaction is AI estimated with the most efficient in prediction AI algorithms. However, this seems not to be the case.

Our results, based on using two AI algorithms (Lasso and Random Forest), demonstrate that the AI "expectation" for customer satisfaction will be misinformed and less accurate if the expectation is that the AI-service customer satisfaction will be driven by the same determinants as the human-delivered service without accounting for the importance of being human as part of the utility function of the customer. In fact, when the delivery of service is substituted with an AI-agent on the supply side, the utility function of the individual seems to respond significantly to the mere information that the supplier is non-human even when re-evaluating the identical same service already received. We are confident in these results as timing clearly identifies the treatment effect (provision of the information regarding the AI-nature of the provider) and the subjectivity of the love for being human is clearly identified as the source of the estimation bias, as the "service" evaluated by the respondent is the very same identical piece of music provided to them and the respondents are clearly aware of this.

We show that descriptively, the seeming distributions in the relatively big dataset differed to a marginal extent when comparing the satisfaction with the same service when evaluated as a presumably human and next when re-evaluated as informedly AI-delivered service. AI usually uses big data and it cannot do much analytical and investigative work on the biases of sampling before the estimation. Such sampling biases were revealed for the sample we use here in the work by Tubadji, Huang and Webber (2021). What AI algorithms do is try to compensate for this hurdle of rough knowledge of the reasons why the observations look as they look like, by employing statistical tools for analysing the causal paths in a multitude of observations. This can be restate as using estimation efficiency to overcome the lack of causal knowledge about the model behind the data. While efficiency of course brings higher precision and this helps towards predicting somewhat better the behaviour of interest, our study demonstrates that this higher precision cannot compensate for the lack of accuracy of the model that corresponds to the utility function of the customer.

Even more importantly, the supposedly more efficient algorithm (Random Forest) actually incurred higher degree of error in its predictions (than lasso and OLS) when using the wrong utility function specification for the post-experimental case of customer satisfaction, not correcting for the loss of covering the importance of being human when the service is delivered by an AI agent. This shows that, as we know from complex systems and big data, when there is an error, the more powerful estimators of higher efficiency can actually incur higher errors when the accuracy of the AI model is mis-specified. Put differently, small error with less efficient predictive tools affects less the prediction than the effect of a small accuracy error can cause in the prediction with a more aggressive in terms of precision estimation method. Small errors seem to affect stronger more precise AI-predictions.

Our results need to be triangulated with further tests for the same hypothesis. If our findings are reconfirmed, the implications for the world of AI services, businesses and society at large might be really important.

The results offered in this study are relevant to a host of further research questions which need a series of careful data collection and analysis allowing to cross-check our hypothesis about the importance of being human and its effect on the preferences of people with regard to AI and human based services. Further analysis will be next very relevant to account for cultural differences in the valuation of being human across different geographies and socio-economic groups. This better understanding of the emotional responses of people to AI services and the substitution between human and AI-supply of services can help us construct better emotionally and thus mental health more favourable reality of the more digitized tomorrow. Potential comparisons of the satisfaction with AI in countries with longer experience and higher rate of adoption of AI as Japan can also provide more insight on the dynamics of the CBD mechanism proposed in this study. This will help reveal if some psychological adaptation develops over time. Thus, our here proposed CBD model can serve as a starting point for addressing a host of interesting and relevant further empirical questions about the complexity of the link between culture, emotion and economics with regard to AI.

Compliance with Ethical Standards: The authors declare that they have no conflict of interest.

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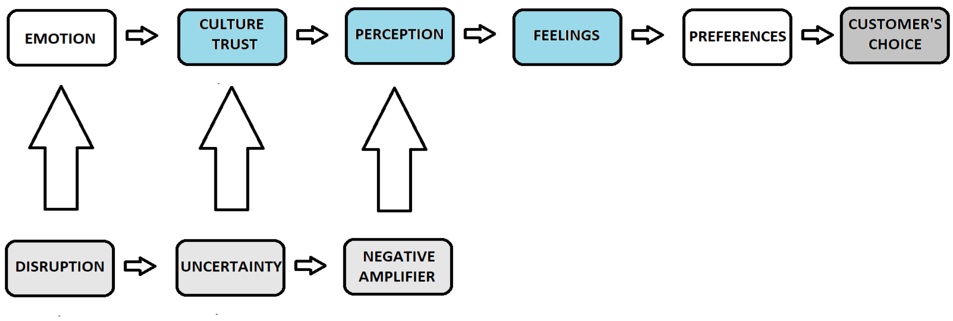


Figure 1: CBD Micro Model for Culture, Emotion and Customer's Choice – Deciding What is Important (Valuable)

Note: The figure represents a visualization of the process of transformation of emotion into customer's choice how to respond to a trigger of their emotions. The process passes through the main upper line of steps. The lower second line of steps capture the effect by exogenous shocks that can cause disruptions to the utility formation process by increasing uncertainty and affecting the formation of perceptions of risk and probability of the outcomes, thus affecting the quality and intensity of feelings which drive the order of preferences in consumer's decision-making process. An example for an application of this CBD mechanism is how a customer decides to value the human nature of the agent that delivers a service. As the customer has evolutionary cultural reasons to perceive the human culturally closer and hence more trustworthy than any other agent (beast or AI), there are strongest positive feelings associated with interaction with a human. Therefore, the latter becomes priorities in the order of preferences for interaction compared to interaction with non-human agents (such as beasts or AI) with whom there is worse or less evolutionary cultural heuristics of trust and cooperation.

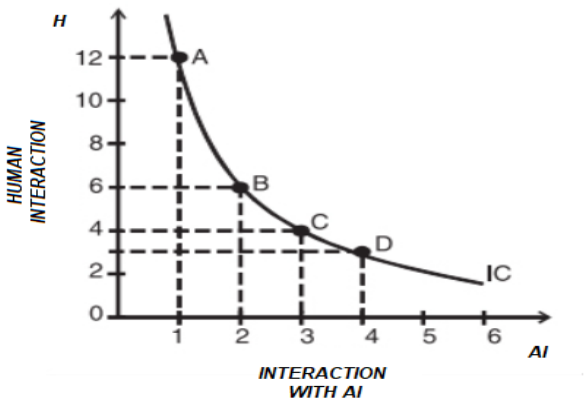


Figure 2: Substitution in the CBD Mechanism of the Importance of Being Human

Note: The figure represents the dynamics in the process of substitution of human service (which contains human interaction) and AI-based service (which cannot provide the human interaction component). As the AI interaction service cannot provide the human interaction component 1:1, because the delivering agent is non-human in nature, the two services are imperfect substitutes. Hence, from economic theory we know that their substitution will follow the laws of a convex indifference curve as presented above. From the properties of a convex indifference curve, it follows that the more AI interaction with AI service is consumed by the customer, the less human interaction the customer will be willing to forgo for one more unit of AI service. Compare point A to point C on the figure above. The customer requires 12/1 substitution between AI and human service when having only 1 AI service (in point A) and then the same customer requires 4/3 substitution ratio when having 3 units of AI service in point C. Put differently, the more services become AI based in the economy, the more the importance of being human grows as weight in the utility function of the customer.

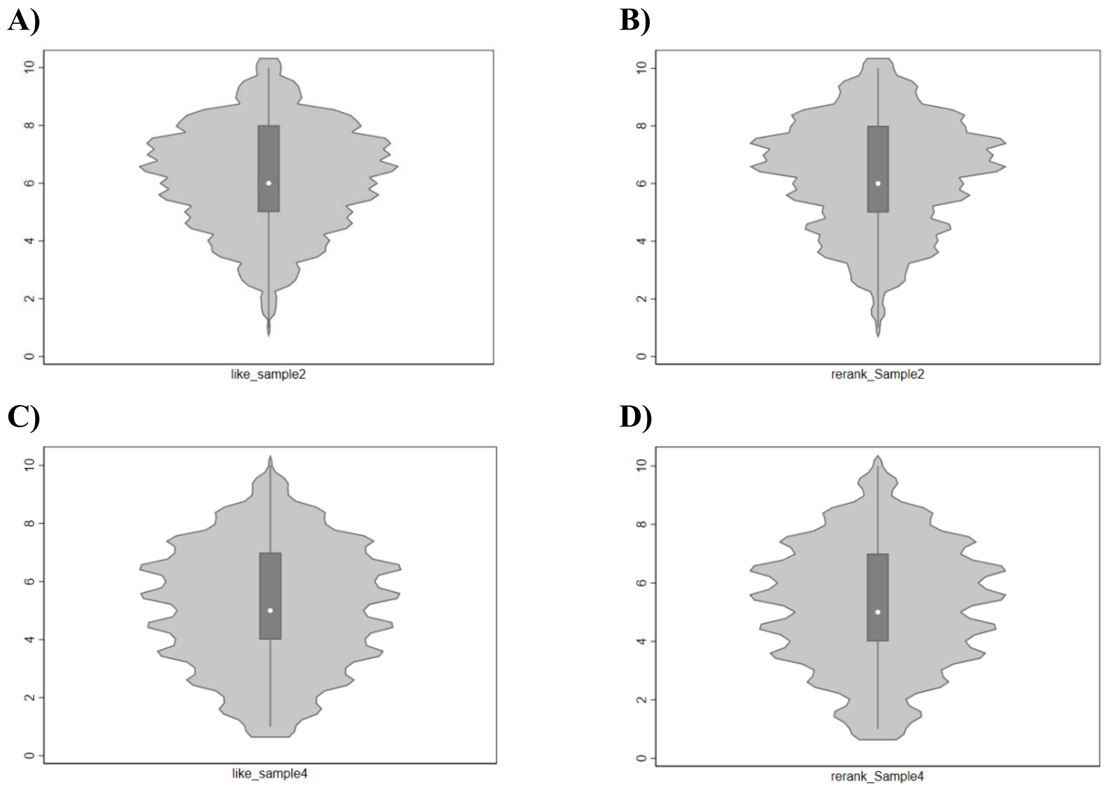
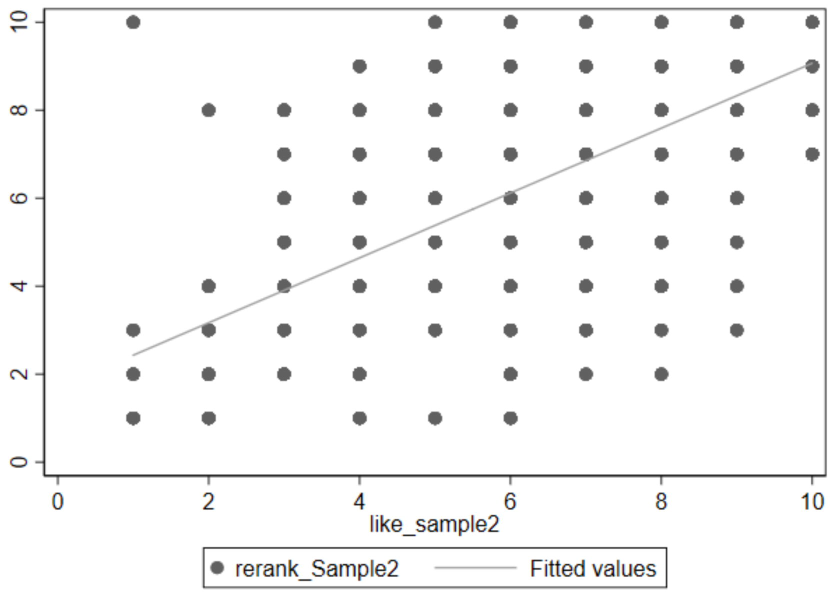


Figure 3: Violin Plots of Consumer's Emotions Pre and Post AI-Awareness Experiment

Notes: The violin plots represent the distribution of the experimental survey respondents' satisfaction with the same piece of music before and after the treatment (information about the AI nature of the composer) was delivered to them. The plots are used to compare the distributions between the pre and post-treatment for sample 2 (plots A and B) and for sample 4 (plots C and D). The inconsistency in the shape of peaks, valleys, and tails of each group's density curve signals differences in the overall distribution of the customer satisfaction after the information-treatment regarding the AI-composer was delivered to the respondent.

A)



B)

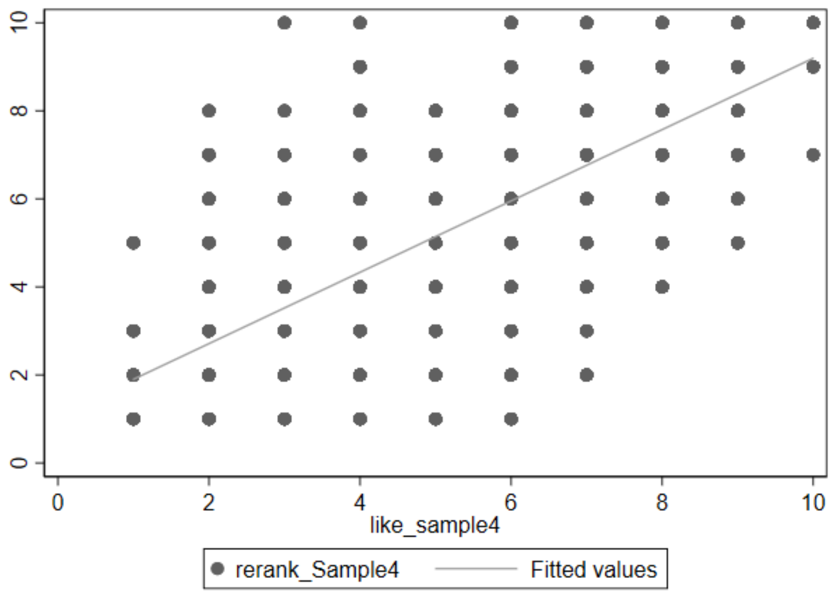


Figure 4: Consistency of Consumer's Emotions Pre and Post AI-Awareness Experiment

Notes: The figure presents the fitted regression line visualized as an illustration of the degree of correlational association between the pre- and post-treatment evaluation of the same sample of music by the participant in the experimental survey. Figure 3A represents the comparison for sample 2 and Figure 3B represents the comparison for sample 4. The best fit would be represented by dots very closely distributed along the fitted line.

Table 1 – Lasso Estimations

	Spec. 1	Spec. 2		Spec. 3	Spec. 4		Spec. 5	Spec. 6		Spec. 7	Spec. 8	
	OLS	Lasso		OLS	Lasso		OLS	Lasso		OLS	Lasso	
dep. Var.	like_sample2	like_sample2		rerank_sample2	rerank_sample2		like_sample4	like_sample4		rerank_sample4	rerank_sample4	
model selected by EBIC		lambda=8.8669			lambda=12.9763			lambda=4.1990			lambda=13.3297	
		Lasso_Adaptive	Post-est OLS		Lasso_Adaptive	Post-est OLS		Lasso_Adaptive	Post-est OLS		Lasso_Adaptive	Post-est OLS
	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
age	-0.008 **	-0.007 ***	-0.008 ***	-0.012 ***	-0.012 ***	-0.014 ***	-0.008 ***	-0.005 ***	-0.006 ***	-4.000 ***		
male	-0.256 ***	-0.231 ***	-0.260 ***	-0.315 ***	-0.297 ***	-0.336 ***	0.081			4.090 ***	0.125 ***	0.241 ***
yes_musician	-0.335 ***	-0.300 ***	-0.343 ***	-0.277 ***	-0.209 ***	-0.274 ***	-0.180 ***	-0.124 ***	-0.150 ***	-0.860		
high_edu_music	0.371 ***	0.292 ***	0.358 ***	0.191 *			-0.053			-1.870		
pop_num	0.197 ***	0.144 ***	0.170 ***	0.206 ***	0.131 ***	0.208 ***	0.342 ***	0.312 ***	0.315 ***	8.900 ***	0.343 ***	0.402 ***
rock_num	0.281 ***	0.213 ***	0.263 ***	0.290 ***	0.185 ***	0.249 ***	0.022			-1.180	-0.052 ***	-0.205 ***
hiphop_num	0.274 ***	0.228 ***	0.244 ***	0.097			-0.044			0.810		
electronicdance_num	-0.073			-0.029			0.218 ***	0.194 ***	0.214 ***	3.050 ***	0.134 ***	0.220 ***
rb_num	-0.048			-0.236 ***	-0.094 ***	-0.224 ***	0.133 **	0.073 ***	0.114 ***	3.110 ***		
indie_num	-0.039			-0.069			-0.156 ***	-0.112 ***	-0.153 ***	-0.170		
classical_num	-0.085			-0.152 **	-0.061 ***	-0.157 ***	0.040			-3.740 ***	-0.129 ***	-0.221 ***
easy_num	0.273 ***	0.183 ***	0.235 ***	0.316 ***	0.216 ***	0.311 ***	-0.069			-0.410		
jazz_num	-0.138			-0.158			0.039			-4.220 ***		
income	-0.031 *	-0.019 ***	-0.032 ***	-0.016			0.018			1.680		
melody_sample1	0.078 ***	0.078 ***	0.083 ***	0.070 ***	0.072 ***	0.080 ***	0.303 ***	0.313 ***	0.308 ***	3.610 ***	0.328 ***	0.312 ***
harmony_sample1	0.117 ***	0.124 ***	0.122 ***	0.119 ***	0.142 ***	0.134 ***	0.126 ***	0.121 ***	0.121 ***	-1.040		
rhythm_sample1	0.089 ***	0.091 ***	0.090 ***	0.029			0.124 ***	0.120 ***	0.122 ***	3.090 ***	0.074 ***	0.091 ***
overall_sample1	0.224 ***	0.236 ***	0.224 ***	0.229 ***	0.239 ***	0.232 ***	0.351 ***	0.360 ***	0.350 ***	1.310	0.459 ***	0.433 ***
coherent_sample1	0.040 *	0.014 ***	0.035 ***	0.129 ***	0.116 ***	0.129 ***	0.043 *	0.028 ***	0.044 ***	3.600 ***	0.013 ***	0.048 ***
_cons	3.514 ***	3.452 ***	3.462 ***	3.426 ***	3.359 ***	3.426 ***	-0.275 *	-0.210 ***	-0.184 ***	14.750 ***	-0.054 ***	-0.132 ***
N	3732	3732		3732	3732		3732	3732		3732	3732	
R2	0.257	0.259		0.224	0.219		0.599	0.598		0.111	0.472	

Notes: The table represents a comparison between the OLS and Lasso-Adaptive Estimations and Post-estimation OLS results. The main focus of analysis is the level of parsimonious state of the model and the overall goodness of fit of the estimation, as these aspects can serve as indicators for the comparability between the models in terms of adequacy with which they capture the utility function of the customer from the sample of music under analysis.

Table 2 – Random Forest Estimations

rforest	like_sample2	rerank_sample2	like_sample2	rerank_sample2
scalars:				
e(Observations):	3828	3828	3828	3828
e(features):	19	19	19	19
e(Iterations):	100	100	100	100
e(OOB_Error):	**0.102**	**0.117**	**0.123**	**0.147**
macros:				
e(cmd):	rforest	rforest	rforest	rforest
e(predict):	randomforest_predict	randomforest_predict	randomforest_predict	randomforest_predict
e(depvar):	rerank_sample2	rerank_sample2	like_sample4	rerank_sample4
e(model_type):	random forest regression	random forest regression	random forest regression	random forest regression
matrices:				
e(importance):	19 x 1	19 x 1	19 x 1	19 x 1

Notes: The table presents the post-estimation results for each of the random forest estimations performed for the pre- and post-experimental evaluation of music samples 2 and 4. The OOB_Error notation stands for the out of bag error for the corresponding model.

Appendix 1: Descriptive Statistics of Main Variables

Model Component	Variable	Definition	Obs	Mean	Std. Dev.	Min	Max
Valuation of Artificial Intelligence (VAI)	like_sample1	Likert-scale evaluation of sample 1	957	5.85	1.99	1	10
	like_sample2	Likert-scale evaluation of sample 2	957	6.13	1.96	1	10
	like_sample3	Likert-scale evaluation of sample 3	957	5.28	2.34	1	10
	like_sample4	Likert-scale evaluation of sample 4	957	5.15	2.18	1	10
	pref_1	Stated preference for sample 1 over 2	957	0.40	0.49	0	1
	pref_3	Stated preference for sample 3 over 4	957	0.54	0.50	0	1
	rerank_like_sample1	Likert-scale re-evaluation of sample 1 after info on AI	957	5.95	2.25	1	10
	rerank_like_sample2	Likert-scale re-evaluation of sample 2 after info on AI	957	6.21	2.09	1	10
	rerank_like_sample3	Likert-scale re-evaluation of sample 3 after info on AI	957	5.55	2.45	1	10
	rerank_like_sample4	Likert-scale re-evaluation of sample 4 after info on AI	957	5.26	2.32	1	10
Taste	age	real age of the respondent	957	26.67	10.54	14	72
	male	dummy variable equal to 1 if respondend is male	957	0.66	0.47	0	1
	pop	dummy variable equal to 1 for self-reported taste for pop music	957	0.46	0.50	0	1
	rock	dummy variable equal to 1 for self-reported taste for rock music	957	0.65	0.48	0	1
	hiphop	dummy variable equal to 1 for self-reported taste for hip-hop music	957	0.38	0.49	0	1
	electronic music	dummy variable equal to 1 for self-reported taste for electronic music	957	0.34	0.47	0	1
	rb	dummy variable equal to 1 for self-reported taste for RB music	957	0.29	0.46	0	1
	indie	dummy variable equal to 1 for self-reported taste for Indie music	957	0.47	0.50	0	1
	classical music	dummy variable equal to 1 for self-reported taste for classical music	957	0.46	0.50	0	1
	easy	dummy variable equal to 1 for self-reported taste for easy music	957	0.17	0.38	0	1
	jazz	dummy variable equal to 1 for self-reported taste for jazz music	957	0.13	0.33	0	1
	income	self-reported income category, where 4 is anchored as national minimum wage level	957	4.93	2.24	1	10
	musician self-identified	dummy variable equal to 1 for self-reported status of a professional musician	957	0.79	0.41	0	1
	music_family	dummy variable equal to 1 if there is another member in the family also playing music	957	0.66	0.47	0	1
	low_edu_music	denotes people with no, limited or only basic understanding of music theory	957	0.45	0.50	0	1
Quality of Creativity	melody_sample1	evaluation of the quality of the sample 1 with regard to melody (Likert scale from 1-10)	957	4.62	1.93	1	10
	harmony_sample1	evaluation of the quality of the sample 1 with regard to harmony (Likert scale from 1-10)	957	5.03	1.95	1	10
	rhythm_sample1	evaluation of the quality of the sample 1 with regard to rythm (Likert scale from 1-10)	957	4.70	2.10	1	10
	overall_sample1	evaluation of the quality of the sample 1 as overall presentation (Likert scale from 1-10)	957	6.32	1.92	1	10
	coherent_sample1	evaluation of the quality of the sample 1 with regard to coherence (Likert scale from 1-10)	957	7.22	1.96	1	10
	melody_sample2	evaluation of the quality of the sample 2 with regard to melody (Likert scale from 1-10)	957	5.22	2.17	1	10
	harmony_sample2	evaluation of the quality of the sample 2 with regard to harmony (Likert scale from 1-10)	957	5.39	2.04	1	10
	rhythm_sample2	evaluation of the quality of the sample 2 with regard to rythm (Likert scale from 1-10)	957	5.13	2.24	1	10
	overall_sample2	evaluation of the quality of the sample 2 as overall presentation (Likert scale from 1-10)	957	6.84	1.75	1	10
	coherent_sample2	evaluation of the quality of the sample 2 with regard to coherence (Likert scale from 1-10)	957	7.29	1.77	1	10
	melody_sample3	evaluation of the quality of the sample 3 with regard to melody (Likert scale from 1-10)	957	5.15	2.15	1	10
	harmony_sample3	evaluation of the quality of the sample 3 with regard to harmony (Likert scale from 1-10)	957	4.83	2.19	1	10
	rhythm_sample3	evaluation of the quality of the sample 3 with regard to rythm (Likert scale from 1-10)	957	6.03	2.27	1	10
	overall_sample3	evaluation of the quality of the sample 3 as overall presentation (Likert scale from 1-10)	957	6.17	2.04	1	10
	coherent_sample3	evaluation of the quality of the sample 3 with regard to coherence (Likert scale from 1-10)	957	6.74	2.00	1	10
	melody_sample4	evaluation of the quality of the sample 4 with regard to melody (Likert scale from 1-10)	957	5.48	2.00	1	10
	harmony_sample4	evaluation of the quality of the sample 4 with regard to harmony (Likert scale from 1-10)	957	4.95	2.11	1	10
	rhythm_sample4	evaluation of the quality of the sample 4 with regard to rythm (Likert scale from 1-10)	957	5.84	2.08	1	10
	overall_sample4	evaluation of the quality of the sample 4 as overall presentation (Likert scale from 1-10)	957	6.13	1.97	1	10
	coherent_sample4	evaluation of the quality of the sample 4 with regard to coherence (Likert scale from 1-10)	957	6.57	1.97	1	10
Cultural Proximity (cultural distance of degree 1 - human vs non-human)	AI	dummy variable denoting that the sample is generated by artificial intelligence (AI)	3828	0.50	0.50	0	1

Notes: The table presents the main descriptive statistics for the variables in our experimental survey.

Appendix 2: Best Performing Model in Lasso, Selected by EBIC Criterion

SAMPLE 2

lasso2	like_sample2						lasso2	rerank_sample2					
Knot|	ID	Lambda	s	L1-Norm	EBIC	R-sq	Knot|	ID	Lambda	s	L1-Norm	EBIC	R-sq
1|	1	1228.0	0	0.00	4920.9	0.00	1|	1	1238.6	0	0.00	5473.3	0.00
2|	2	1118.9	1	0.03	4833.9	0.03	2|	2	1128.6	1	0.04	5388.7	0.02
3|	12	441.3	2	0.26	4393.1	0.14	3|	14	369.6	2	0.30	4952.0	0.13
4|	18	252.5	3	0.38	4188.1	0.18	4|	21	192.7	3	0.42	4804.2	0.17
5|	26	120.0	4	0.48	4065.3	0.21	5|	28	100.5	4	0.51	4746.9	0.18
6|	28	99.6	5	0.53	4051.5	0.22	6|	29	91.5	5	0.56	4743.7	0.19
7|	29	90.8	6	0.57	4047.1	0.22	7|	31	76.0	6	0.63	4724.5	0.19
8|	31	75.3	7	0.68	4028.9	0.22	8|	35	52.4	8	0.76	4700.3	0.20
9|	34	57.0	8	0.87	4002.0	0.23	9|	36	47.7	9	0.83	4698.9	0.20
10|	37	43.1	11	1.10	3995.7	0.24	10|	37	43.5	10	0.92	4695.6	0.21
11|	39	35.8	12	1.32	3980.3	0.24	11|	45	20.7	12	1.44	4665.6	0.22
12|	45	20.5	13	1.78	3944.6	0.25	12|	51	11.8	13	1.83	4655.3	0.22
13|	49	14.1	14	1.98	3938.8	0.25	13|	52	10.8	14	1.90	4661.0	0.22
14|	55	8.1	15	2.20	3935.7	0.26	14|	53	9.8	15	1.97	4666.9	0.22
15|	58	6.1	16	2.30	3940.2	0.26	15|	60	5.1	16	2.31	4665.6	0.22
16|	65	3.2	17	2.49	3943.8	0.26	16|	62	4.2	17	2.38	4672.1	0.22
lasso2,	lic(ebic)						lasso2,	lic(ebic)					
lambda=8.86	(selected	by		EBIC).			**lambda=12.97**	(selected	by		EBIC).		

SAMPLE 4

lasso2	like_sample4						lasso2	rerank_sample4					
Knot	ID	Lambda	s	L1-Norm	EBIC	R-sq	Knot	ID	Lambda	s	L1-Norm	EBIC	R-sq
1|	1	3405.9	0	0.00	5842.3	0.00	1|	1	3885.7	0	0.00	6288.4	0.00
2|	2	3103.3	1	0.07	5562.9	0.07	2|	2	3540.5	1	0.06	6046.3	0.06
3|	4	2576.4	2	0.19	5024.5	0.20	3|	11	1532.6	2	0.44	4844.2	0.32
4|	30	229.4	3	0.86	2777.5	0.56	4|	39	113.3	3	0.86	4043.3	0.46
5|	32	190.4	4	0.88	2736.6	0.57	5|	46	59.1	4	1.05	4013.4	0.46
6|	37	119.6	5	0.92	2656.4	0.58	6|	52	33.8	5	1.15	3997.5	0.46
7|	49	39.2	6	1.20	2552.7	0.59	7|	53	30.8	6	1.18	4001.1	0.47
8|	56	20.4	8	1.36	2544.2	0.59	8|	54	28.1	7	1.24	4001.9	0.47
9|	59	15.4	9	1.43	2541.5	0.60	9|	59	17.6	9	1.49	3993.8	0.47
10|	62	11.7	10	1.52	2540.1	0.60	10|	63	12.1	10	1.71	3984.7	0.47
11|	63	10.6	11	1.55	2544.2	0.60	11|	64	11.1	12	1.76	3997.2	0.47
12|	74	3.8	13	1.79	2542.1	0.60	12|	68	7.6	13	1.95	3993.2	0.47
13|	82	1.8	14	1.92	2544.6	0.60	13|	71	5.8	14	2.05	3995.3	0.48
14|	88	1.0	15	2.00	2551.1	0.60	14|	74	4.4	15	2.13	3999.0	0.48
15|	89	0.9	16	2.02	2559.0	0.60	15|	75	4.0	16	2.17	4005.7	0.48
16|	90	0.9	17	2.04	2566.8	0.60	16|	80	2.5	17	2.33	4009.0	0.48
lasso2,	lic(ebic)						lasso2,	lic(ebic)					
lambda=4.19	(selected	by		EBIC).			**lambda=13.32**	(selected	by		EBIC).		

Notes: The table shows the Lasso knots used to display and identify the selected best performing model according to the EBIC criterion, i.e. the model with minimum EBIC value. The main statistics for the performance of each model knot are stated, along with the corresponding lambda for the model.