Cultural Proximity Bias in AI-Acceptability: The Importance of Being Human

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Artificial intelligence (AI) can generate a greater number of recombinations of ideas than humans can, and hence AI-produced creative products could be seen as embodying more innovation and surprise which are worth higher economic value. Yet the lack of human emotionality embedded in an AI product deprives it of an essential 'humanness' to which people attach important cultural value. As the overall value of a product is a sum of its economic and cultural values, we assessed the demand differential and quality perception asymmetry of creative products, specifically music compositions, that have been created by humans and AI separately. We conducted a survey with a quasi-experimental design and found that respondents reveal lower valuations towards music generated by AI and will moderate their evaluations of quality away from AI- and towards human-generated compositions when the type of composer is known. The demand for creative goods is sensitive to consumers' perceptions of cultural proximity to humanness that determine the acceptability of AI on the market.

SER Keywords: Culture; Valuation; Preferences

JEL Keywords: AI; creativity; cultural proximity; cultural value; preferences.

JEL classification: Z10; J23; J24; J17; O33.

"The cost of a thing is the amount of what I will call life which is required to be exchanged for it, immediately or in the long run" H. D. Thoreau, *Walden*

1. Introduction

One of the fundamental characteristics that remains unattainable for AI is the ability to relate to human emotions, and above all the ability to have appropriate intuitions about moral attitudes and values, i.e. the *essence* of being human. Marx (1867, p.130) shed light on the fact that "all commodities are merely definite quantities of congealed labour-time" and Lutz (1995) appreciated that what people ultimately value is the time and dignity of their human life. Economic research rarely considers the role of human dignity in economic behaviour because it is assumed to be self-evident in a human reality, but this is becoming an increasingly pertinent issue that is challenged at the dawn of the AI revolution. From an evolutionary economics perspective, the cost of crafting creative outputs is not only money but also time, which is scarce, not substitutable and irrecoverable, i.e. the *time* of a human life. This valuation of the time of a human life underpins the cultural valuation of goods and services, which Throsby (2001) defines as the value perceived by the consumer in addition to the economic value of materials necessary for its production. This article seeks to identify whether demand functions only include objective attributes of innovative products, in which case AI and human innovations could have equal value to the consumer, or whether the contribution of human time embodied in goods and services and delivered by humans have their own cultural value, in which case human-generated products could have a greater cultural value relative to AI-generated equivalents even when their objective attributes appear indifferentiable or inferior.

The fear of and enthusiastic support for artificial intelligence (AI) reflect fast thinking about AI. How AI affects human opportunities in the labour market will depend on whether AI possesses technologies that complement human creativity or whether AI possesses the full set of human characteristics and becomes a true substitute (Korinek and Stiglitz, 2017). Yet, even though AI ostensibly increases efficiency, paradoxically AI seems to be associated with stagnating growth (Brynjolfsson *et al.*, 2017). Labour economics has contributed prolifically to our understanding of the interplay between AI and economic development (i.e. Autor *et al.*, 1998; Murnane, 2004; Brynjolfsson and McAfee, 2011; Katz and Margo, 2012; Michaels *et al.*, 2014) and the substitutability of AI for humans within tasks (Autor, 2013; Autor and Dorn, 2013; Arntz *et al.*, 2017; Acemoglu and Restrepo, 2017) or within occupations (Fry and Osborn, 2017). This can be summarised as a fear that education can no longer shield people in the labour market in the new AI era (Busemeyer, 2012). However, labour economic concerns regarding AI are likely to be driven by pure human fear, as people who are more likely to be affected by AI are found to be more concerned about AI and its impact on the labour market (Emmenegger, 2009; Mau *et al*., 2012; Dekker *et al*., 2017).

The literature also documents that fear of AI, especially experienced by workers afraid of losing their jobs, instigates bounded human behaviour due to technological anxiety (Arntz *et al.*, 2016, 2017; Gregory *et al.*, 2016; Mokyr *et al.*, 2015; Autor, 2015). It is surprising, therefore, that the literature has paid little attention to consumers' technological anxieties towards AI-produced goods, and the differences in the elasticity in demand between AI- and human-generated goods (Bessen, 2018). Where consumers' technological anxieties have been the foci of attention, there has been only partial recognition of peoples' needs for empathy in sectors such as health care (Fogel and Kvedar, 2018; Levy, 2018) and findings are generally inconclusive about the role of cultural value in shaping demand and choice.[1] Rather than recognizing the importance of humanness in the utility function, economic debate is dominated by discussions about the importance of AI for socio-economic welfare that are grounded on speculations that AI will ensure economic opportunities for universal income and an utopian life where machines work while people experience leisure time and nurture their creative abilities. However, this utopia depends on the responsiveness of demand to AI-produced goods and services and does not consider only economic value.

This study is also the first to focus on the reasons for demand resistance towards AI-generated goods when goods embody human creativity. There is a relatively new stream of contributions on the role of AI-acceptability, as a different determinant of AI-adoption, that has its own role beyond the AI-product-quality (Nadarzynski et al. 2019). Our novel contribution to this stream of literature is that we identify precisely through a special experimental design a particular type of cultural bias driven by the perception of importance of being human, and we analyse the latter from the point of view of its economic mechanism and socio-economic implications. Namely, we propose that there is a strong evolutionary mechanism favouring cultural proximity in economic choice, which stimulates 'home bias' in consumer choice. We explain the preferences for cultural value in human-made products that are associated with cultural proximity between human consumers and producers, which can be explained by the recognition that humans use their time to express their sublime emotional essence in a creative product. Thus, every consumer's utility function contains not only objective economic values relating to the production cost of a good, but also cultural economic values relating to the human time and sentiment embodied in the good, with

[1] Some studies (e.g. HSBC, 2018) suggest that people prefer interaction with AIs over humans in areas like healthcare (specifically when receiving heart surgery) and yet prefer to trust humans over AI robo-advisory services when receiving advice about banking decisions; other studies explain these findings by suggesting that interaction with humans on personal finance issues is an exception that is conditioned by social capital and local cultural milieu (Tubadji *et al.*, 2019). In general, the literature overlooks the importance of human interaction and maintains that preference for human interaction reflects old-fashioned fears.

cultural economy value being especially relevant for creative goods (Throsby, 2001; Turner and Lourenço, 2012). When human-made and AI-generated goods compete in tandem so a novel situation appears where the cultural value of both types of products differs due to the identity of the products' producers. Here, consumers have a higher cultural proximity to human producers because of their human identity and therefore they can be expected to perceive that human-made goods possess a higher cultural value relative to AI alternatives.

From Adam Smith through to moral philosophy and to modern models of trade flows, the role of cultural proximity (i.e. the preference for things closer to your own identity) is a well-known natural characteristic of human socio-economic behaviour (Zhou, 2011; Tubadji and Nijkamp, 2015; Fisman *et al.*, 2017). Keynes (1930, 1936) and Feduzi (2010) argued that cultural proximity acts as a weighting of people's preferences that is integral to the human utility function and biases the rational function of choice that focuses on objective product attributes. Although AI-generated products may incur lower production costs and have better objective performance attributes relative to human-produced alternatives, the lack of cultural proximity of an AI-generated product may lead consumers to discount it. The literature in marketing and management has broadly attempted to document this, yet the experimental designs are rarely sufficient to identify the effect clearly and the economic implications are largely under-estimated and there is in practice insufficient awareness of the important economic consequences for AI producers. Our study addresses this gap, by offering a carefully tailored experimental design that allows us to precisely identify the role of the importance of being human in the utility function of the consumer and the discrimination towards AI-produced services associated with the same customer's taste.

To test this hypothesis we focus on a particular creative good, musical compositions: music is known to be an especially important artistic expression of human imagination that affects the state of the human brain and the development of human cognition (McCarthy, 1985; Karageorgis *et al.*, 1999; Jourdain, 2008; Rose *et al.*, 2019). We ran a survey embedded with a quasi-experimental within-group design to collect primary data that reflects respondents' preferences for the nature of a music composer (human versus AI). We then analysed the components of the utility function by comparing responses collected when the respondent was and was not informed whether the composer was human or AI. Our results indicate that knowledge of a composer being an AI rather than a human resulted in a lower utility and decreased preference for the AI product, which highlights the importance of cultural proximity to the consumer and the evolutionary human need for human-produced creative products. Moreover, this cultural valuation bias towards the humanness of the creative product was expressed in a readjustment of analytical thinking by participants rather than being a simple fast thinking effect.

The remainder of this paper has the following structure. Section 2 presents a review of the literature on the degree of complementarity of humans and AIs in tasks, occupations and the creative sector and the importance of cultural proximity bias that underpins choice. Section 3 details a Culture-Based Development (CBD)-inspired hedonic valuation model, where the utility derived from a creative product is explained by individual taste, product attributes and cultural proximity. Section 4 describes the estimation strategy and section 5 presents the results. Finally, section 6 presents a discussion of the generalizability of the results, outlines implications of including cultural proximity in a consumer's utility function, and explores the consistency of translating this utility into explicit preferences and choices.

2. Artificial intelligence, creativity and cultural proximity

Labour economics research into the effects of AI assesses whether AI is either a valid substitute or a complementary tool for human labour. Although at this early stage it is difficult to test empirically the validity of any AI-related claim, research has narrowed to two types of studies. On one hand, the observed substitution of human labour by AI in specific tasks is used to validate claims that AI has efficiency gains in the production process (Arntz *et al.*, 2017) and justifies further technical innovations and more R&D (Cockburn *et al.*, 2018). On the other hand, the responsiveness of demand to AI-related innovations is analysed and forecasts made concerning which sectors will experience greater AI/human substitution (Fry and Osborn, 2017) with preferences for AI being captured using survey instruments albeit typically ignoring mechanisms that underpin demand profiles.

Demand profiles for AI-generated goods may differ from demand profiles for human-generated goods due to the hitherto underappreciated cultural valuation underlying informed convictions that shape market behaviour. Efficiency is important and a necessary element of creativity, but the quality and value of creativity is shaped by and reflects cultural values that are determined by social and cultural forces encapsulated in the notion of cultural proximity.[2] Cultural proximity is a natural element that orchestrates economic choice and reproduces evolutionary mechanisms that set boundaries for economic behaviour in the forms of tastes and needs. Thus, tastes for AI-related goods cannot safely disregard or perturb culturally proximate factors simply to conform to pre-AI expectations.

AI Efficiency and Product Quality

Novelty is risky, and the natural evolutionary emotion of fear associated with uncertainty affects the adoption rates of previously untried and untested goods. Prospect theory shows us that fear is a very powerful driver of choice, with the negative influence of fear being twice as strong as the influence of positive expectations (Kahneman and Tversky, 1979) and with

[2] Cultural proximity is the reverse of cultural distance.

people generally preferring what they already have (the so called endowment effect; Thaler, 1980). Very often people disregard creative ideas due to their bounded rationality (Shackle, 1949; Beck and Katz, 2001) with consumer behaviours inhibited by culture to make behaviour predictable and with behaviours being learned and heuristic to save energy and time, enhance efficiencies and regularise experiences.

Novelty in the arts and creative sectors is well known to be victim of what Baumol and Bowen (1966) call the cost disease,[3] where over time art has experienced increasing costs without concomitant improvements in productivity.[4] Thus, increasing rates of innovation by AI may be very beneficial to creative industries but only if cultural value is incorporated into AI-generated products.

For the last two or three decades, AI developers have insisted on the question whether AI can create products as good as humans (i.e. to generate product that is so surprizing that it can trigger emotion as art is supposed to do) and some have argued AI can even exceed human capability to generate surprising results (see Marsden 2000). The true question, however, especially from economic markets point of view, might as well be whether humans can ever view AI products as truly creative ones, no matter how good quality the AI products are, as there seems to be a bias favouring human creativity, even among the AI developers and their perceptions of what is creative (Audry and Ippolito 2019), which determines the acceptability of the AI on the market in a biased towards being human manner (see for example Morley et al. (2021).

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3 The essence of this cost disease is essential in understanding economic phenomena more broadly and is part of the discussion surrounding the Balassa-Samuelson effect and purchasing power parity that remains largely unexplained. See Tubadji and Nijkamp (2018) for a discussion of the connections between culture and the Balassa-Samuelson effect.

4 Empirical support for the existence of the cost disease was provided by Felton (1994). Frey (1996) claimed that although the disease persists for conventional arts venues, innovation in the festival sector manages to overcome this disease.

Meanwhile, the price of creative goods reflect two issues: economic value, which depends on material and functional attributes, and cultural value, which reflects how people perceive the importance of the good in their social context (Throsby, 2001). We argue here that the demand for any good contains elements of both economic and cultural value, and this is only especially visible in the consumption of art products that embody the highest quantity of expressions of cultural and social norms and attitudes.

Artists supply entities that require material inputs (reflected in economic value) and anticipate supernormal profits associated with the product's social desirability (cultural value) (Snowball, 2008). Mechanisms that conceive cultural value vary across products but include status symbols (Veblen, 1899; Belk, 1988, 2016; Luna-Cortes, 2017), altruistic needs incorporated in corporate social responsibilities (Porter and Kramer, 2019), and uniqueness of expression / ideas / experiences that make the product more desirable (Holler and Peters, 1999; Marciano and Moureau, 2013).

Consumers' demand is driven primarily by basic needs (Farber *et al.*, 2002) but intrinsic and extrinsic needs informed by cultural values also induce demand. The extrinsic drive for demand is motivated by social desirability which will bestow social attractiveness to the individual possessing the good through magical contagion (i.e. if you possess a socially desirable product then you are a socially desirable person; Fernandez and Lastovicka, 2011). Intrinsic cultural motivations also underpin demand and constrain choice by steering emotions relating to urgency and time scarcity (Westbrook and Oliver, 1991). Monetary payments are palpable representations of power to exchange in the market that are obtained in return for time and energy sold in the market as labour (Marx, 1867) and the purchased product reflects that solidified time and creative energy of the human labourer that produced the good; the latter property becomes especially pertinent in creative art products because art's cultural value is a public expression of the strength of the emotions that we can relate to that are embedded in an artwork by other human beings; the more scandalous the emotion so the more rare and culturally valuable the item becomes.[5]

Price assessments that focus squarely on stated preferences and willingness to pay skew the focus towards an economic value of life. In contrast, the valuation of time and dignity are cultural values that people handle separately in their mental accounting. Although Throsby (2002) contends that a product's economic and cultural values should be considered concomitantly in a consumption function, in practice this is problematic because a willingness to pay survey could identify the economic value but the cultural value of the product needs to be questioned separately if demand behaviour is to be predicted with accuracy (Khalid and Helander, 2006). For example, a rational modern person of average market experience would consider the economic value of genuine leather boots to be higher than the price for faux leather boots and may be still be willing to pay more for genuine leather based on their market experience. However, this will not reflect the cultural value the person bestows on animal life and the person may still be inclined to prefer faux leather rather than genuine leather.[6]

The essential element of cultural value is that it triggers consumers' emotions and thus every consumption of a product that contains cultural value is an expression of bounded rationality, where magical beliefs enact socially desirable contagion through the possession of socially desirable goods (Shweder, 1977). Emotion, as known from social psychology and

[5] The relationship between rarity and cultural value is non-linear and defined by inflection points. First, the more scandalous an idea is then the less it is acceptable to society, because greater association with scandalous ideas decrease social desirability. Gradually, however, the spread of the scandalous idea reaches a tipping point, where the scandal begins to be perceived as a novelty, which then becomes socially desirable for a certain group where this scandal has cultural meaning. From this point onwards, the spread of the scandalous idea amplifies the popularity and increases the demand for the fashionable novel scandalous idea. However, once the number of people accepting the idea as socially desirable reaches a threshold and the acceptability of the idea spreads virally among the entire population, so the economic cost increases with scale but the cultural value decreases due to a reduction in novelty.

[6] Even if a questionnaire on willingness to pay tries to distinguish between aspects of fair prices and willingness to pay, simply using the phrase 'price' will bias the respondent towards thinking of economic value rather than cultural value.

Sigmund Freud, is a disturbance of the status quo perception of reality and a registration in our cognitive system that something novel is at stake and demands our attention (Rieff, 1956; Turner, 2006). We do need to give attention to novel triggers because they may represent danger, so a pure survival need naturally explains our interest in novelty. The extent of social desirability embedded in a novelty is signalled to us from our group and reflects the partial or extensive social perception that the novelty could be a benefit or a threat to our survival. In other words, novelties embodied in a product stir emotions while social desirability associated with the product confirms this emotion as a positive feeling. AI is undoubtedly superior to humans in identifying new combinations of attributes, and hence can create more novelties (Hutter, 2011), but this does not mean that the novelty will be socially desirable.

Cultural Proximity Bias in Perception of Quality

The AI-related literature which stumbled over the puzzle of human perceptions was prominently seen with regard to law and decision making (Schafer 2016). The so-called asymmetric relationships literature, explorations of fuzzy sets and alike applied economics and management contributions, delved into how humans' perceptions of fairness can be achieved by a machine in a way more close/proximate to human judgement (Waldfogel1998; Subramani and Venkatraman 2003; Fung et al. 2006; Frye et al. 2019). However, in our study we pose a related yet different question. We want to know how big the cultural human bias towards an AI-driven product is once we hold the performance of the AI as fixed. This is a particularly important question from an economic point of view. While product quality depends of AI performance, market adoption of the AI product depends on the consumer's perception which is not necessarily identical with product quality, especially in the crucial for market diffusion initial stages of the AI product appearance on the market. An over-estimated expectation f market demand based on quality-judgement might lead to over-investment and over-optimistic expectations for financial returns, which will ultimately lead to an AI-investment bubble, that can disappoint and destabilize the AI-investing market for a long time. This can be avoided if the planning for the consumer's perceptions of AI are correctly factored in modelling the market response to AI creative products. The latter developments can affect greatly the AI impact on employment, justly dealt with as a key AI-related question by Frey and Osborne (2017). Put differently, this regards the social desirability of AI-creativity.

The social desirability of a choice is a function of what Adam Smith explains in his Theory of Moral Sentiments as a cultural distance. According to Smith, if I like a cultural good (e.g. a poem or a piece of music) and then you experience and enjoy it, so your positive experience will enhance my utility from consuming it: you, as an individual, will become socially more desirable if your taste is increasingly understood to be only a relatively small cultural distance (and hence a high cultural proximity) from my own taste. This cultural proximity effect is so strong that it can create cognitive dissonance or cognitive consonance.[7] The importance of such homophily is renowned in sociology and related disciplines (McPherson *et al.*, 2001; Jacquemet and Yannelis, 2012; Monier, 2012).

Our cultural proximity is greater towards other humans than it is towards AI. Even if AI passes the Turing test (Turing, 1950) and even if AI can be made to be lifelike, it is an undeniable fact that human life is naturally generated whereas AI is generated by people and will remain artificial (rather than natural). Thus, due to cultural proximity concerns, humans will logically prefer 'natural' human interaction and products over 'artificial' alternatives when otherwise they could be viewed as being equivalent. While one may perceive

[7] Smith also explains with examples how physical distance is inversely related to social desirability and cultural value. For instance, it is socially desirable to be compassionate towards people suffering from an earthquake on the other side of the world, but if you experience a contemporaneous paper-cut then your own mild suffering will be more important to you because the social desirability to be compassionate to their suffering will be diminished due to muffled social pressures and a lack of cultural proximity.

gradations of proximity between oneself and other human beings, one will perceive categorical difference between human and artificial entities even if the entity has otherwise human characteristics.

Thus, it is not simply the novelty generating potential of AI that is important for the contribution of AI to creative industries but also the cultural distance between the consumer and the AI- and human-generated products that will affect the relative demands for their goods. Recent research alludes to the possibility of this link with Fogel and Kvedar (2018) and Levy (2018) both finding that people do not want AI in the health services where social compassion is of high emotional value; these authors also predict that AI will be used less in health services despite greater efficiency gains. People tend to report higher sensitivities to AI in money investment decisions than in health surgery operations but this could reflect money being a solidified form of time. Research into the utility function of robo-advisory services in the banking sector shows that AI is acceptable only when social capital is lower in the context of the individual (Tubadji *et al.*, 2021).[8]

The next section proposes a model that can be used to assess the importance of the supplier of creative products being human since the above literature review suggests that being human may play an important role in the utility function relating to the consumption of a creative product. The proposed model can also assess how people culturally value the artistic creativity embedded within a product when that product is generated by AI rather than natural human intelligence.

3. A hedonic valuation model of the demand for AI

[8] Further research needs to identify whether positive effects from using AI declines expeditiously after its initial adoption in all types of social capital contexts.

It is not a trivial task to model theoretically the utility function, but value-free economics is no longer the best option for economic analysis since the tools and methods for positive study of utility have increased significantly since the 1930s. Nowadays, a Culture-Based Development (CBD) value free analysis of values (i.e. empirical identification of the effect of a cultural value) is the modern approach in economic analysis (see Tubadji 2020). We propose a CBD hedonic valuation model[9] that represents an individual's utility attained from an AI-generated creative product. As every hedonic model, our CBD model has two parts – objective characteristics (in this case music characteristics classified according to standard music theory, which postulates what are the objective characteristics of music, listing them as: melody, harmony, rhythm, comprehensiveness and overall performance (see Toch 1948; Henkin 1955) and the a taste component, which we hypothesize as existing hedonic taste for the importance of being human, which we manage to capture appropriately thanks to the unique experimental design in-built in our survey design. Thus, our CBD hedonic model can be stated as follows:

$$VAI_i = f(Taste_i, Quality\ of\ Creativity_{ij}, CP_{ij}) \quad (1)$$

where i and j signify respectively the individual and cultural group to which the individual belongs, and VAI_i is the valuation of an AI product, which reflects the genuine psychological experienced utility[10] that the individual derives from the product. We intentionally avoid willingness to pay variables because measurement errors in willingness to pay values will be associated with the errors in the income variable. Instead, we use the respondent's reported

[9] Hedonic valuation models are a widely accepted in economics approach for studying customer's self-reported utility and willingness to pay with a long tradition (see Land and Jones 1979; Ekeland et al. 2002; Metzner and Kindt 2017). They are applied for a variety of cases, especially from modelling non-direct property characteristics that are affecting housing prices, such as ecological aspects such as air quality (Bayer et al. 2009), green areas (Morancho 2003) and others.

[10] See Berridge and O'Doherty (2014) for the distinction between experienced utility and decision utility.

experienced utility, measured on a 10-point Likert scale. As we know from behavioural economics, people act not upon their objective interests but upon their bounded rationality driven by their experienced and remembered utility of an activity and then expect the same utility from similar activities. Choice and action are bounded, and perhaps irrational. They are driven by experienced utility and not only by the objective outcome of utility maximization (Kahneman et al., 1997; Kahneman and Krueger, 2006). Hence, it is pertinent to assess the extent that humans' valuation of AI products will be bounded.

$Taste_i$ is a vector of personal characteristics including demographic, economic, and human capital characteristics that shape an individual's tastes. Since Scitovsky (1976), a wealth of consumer research has explicated that demographic and economic characteristics possess crucial explanatory power of an individual's tastes and preferences.

$Quality\ of\ Creativity_{ij}$ is a vector of objective product attributes that can reflect technical efficiency levels, and in our case of musical compositions these include melody, harmony, rhythm, comprehensiveness and overall performance. Finally, CP_{ij} is a vector of cultural proximity which takes the value of 1 (one) when there is higher proximity (i.e. when the composer is of the same identity as the consumer – i.e. human) and equal to 0 (zero) when the composer is of a different nature than the consumer (i.e. an AI 'composer'). CP_{ij} positively (negatively) effects choice when the individual comes from the same (different) cultural identity.[11]

Finally, this model is essentially a type of Culture-Based Development (CBD) model, as it is inspired by the CBD framework (see Tubadji, 2013, 2014), which suggests that human economic choice is driven by individual and aggregate effects of culture. The individual

[11] This cultural proximity effect has a spatial consequence as explained in the works of Akerlof (1997) and Ingelhart and Wenzel (2010) that illustrate the role of cultural proximity for clustering in space due to the sharing of similar cultural attitudes, which is consistent with Adam Smith's (1759) explanation of the importance of homophily and cultural distance in determining economic behaviour. Smith (1759, part 3, chapter 1) states that a geographically distant event (e.g. fatalities due to an earthquake on the other side of the world) will evoke less intense concern than the accidental personal loss of a finger of one's hand.

effect of culture in the model above is the component of individual taste ($Taste_i$) while the aggregate effect of culture is the group identity difference between the respondents to our survey and the composers of the piece of music (CP_{ij}).

4. Data and method

Primary data were collected using a questionnaire where individuals were asked to objectively and subjectively evaluate musical compositions generated by human and AI composers. The questionnaire and descriptions of the full set of variables can be found in Appendices 1 and 2.

Experimental Design

This study sought to recruit a balanced number of self-declared experts and non-experts on music in order to gain insight into cognition-free and emotion driven cultural valuations of the creative aspects of music. The sampling strategy followed a convenience sampling approach[12] using music-relevant groups on Facebook, music-related forums on the Internet, and a random sample of a UK university's students and staff. The data collection was launched on Saturday 30th March 2019 and remained open for the duration of a weekend and into Tuesday, thereby encompassing an 85 hours window. During this time 960 responses were collected of which three were incomplete, and this sample size is greater than the

[12] Our convenience sampling essentially is motivated by the same reasons as snowball sampling technique is used in hard to reach populations (see Biernacki, and Waldorf 1981; Faugier and Sargeant 1997). In our case, given that there were no funds for in lab experiments and MTurk or alike sampling services to be employed, the only way to create the experimental conditions necessary for identifying taste in our analysis is to carry a survey with in-built experimental design and disseminate it online. Meanwhile, convenience and snowball sampling spread through networks which resembles the natural spread of the adoption of technology. Thus, the sampling technique should be especially appropriate to recreate realistic conditions to the questions of interest in our study – the way that the customer network will respond to the substitution between human and AI producers.

recommended size for such an investigation. Nevertheless, there will always be questions regarding saturation and pragmatism, so we suggest that future research should replicate our study to identify the stability, validity and generalisability of the results.

The questionnaire in our online survey followed a quasi-experimental within-group design. In the first stage, respondents were supplied with four pieces of music without any information about the nature of their composers and then they were asked to evaluate the music according to the main known objective components of music (melody, harmony, rhythm, comprehensiveness)[13] and rank their overall performance. Next, the respondents were informed that some of the samples were produced by an AI and they were asked to predict which of the music samples might have been generated by an AI. Next, the respondents were provided with the correct information about which two of the four sets of music were generated by the AI. The respondents were given the opportunity to listen to the compositions again and were then asked to re-rank their views of the overall performance of each composition. The experiment aimed to detect whether there is a significant change in the valuation of music before and after the respondent is aware of the nature of the composer.

AI Music Synthesis: Generating the Treatment in the Experimental Design

The treatment in our experimental design relies on evaluating an AI synthesized music – first without knowing that the composer is Ai and then re-evaluating it after the information has been provided. The reason for this treatment contains the essence of our research question. The application of technology for the purpose of music creation has been around for decades, it greatly enhances composer capabilities and allows them to envisage their imagination. The AI developers concern, and debate has always been focused on

[13] Toch (1948) and Henkin (1955) established these as the main components of music in music theory.

whether AI can be as creative as a human. The main concern that our study raises instead is, in line with Audry and Ippolito (2019) and the very insightful recent book by Hidalgo et al. (2021)[14], that the wrong question is being asked when AI's creativity and art creativity are placed together, especially in economic context. As Audry and Ippolito (2019) allude, whether AI can produce creative products is a question of human perception about what creativity is at the first place. People, and even developers themselves, disagree on whether the AI creativity can be simply labelled as creativity, even when it is very surprising as an outcome. In order tod isentangle human's perception of creativity from the quality of the Ai "creative/artistic" product, we need to synthesize AI music and see how the evaluation of it changes based on the perception changes regarding it being produced by a human or AI composer, without changing the quality of the music itself. The best way to do this is to see how the evaluation of the very same piece of music changes only depending on the changing perception regarding the human versus AI nature of the composer. This approach disentangles empirically the question of quality from the cultural question of the perception that there is some importance of being human associated with defining creativity itself. Meanwhile, we have attempted to be fair with regard to the quality of AI music synthesized.

Since the beginning of the 21st century, the increasing capabilities in computing power and algorithms has allowed a growing number of platforms to be developed for musical composition[15]. Commercially, AI-powered music composers have demonstrated a

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14 Hidalgo (2021) is a recent cutting_edge contribution that indeed compares the attitude of humans towards machines and humans in terms of the mistakes done by both types of 'suppliers'. This research demonstrate that when it comes to mistake again a higher importance is given by customers to human mistakes while AI mistakes are taken more lightly – apparently as expected from prospect theory – the importance of being human magnifies the positive and negative effects relate dto being human. Apparently, in line with prospect theory, negative effect is even more prominent, so punishment for human mistake is also more prominent than for AI just as the appraisal for human creativity is higher for humans. The comparison of positive and negative intensity of the human proximity bias as well its dynamics over time are fruitful avenues for future research.

15 Companies, such as leading company AVIA, Amper Music and Jukedeck can analyse the patterns of tens of thousands previous musical composition in hours and uses deep neural networks to create music in seconds (Zulic, 2019). In the case of AIVA, it stores more than 30,000 music in a MIDI format, which includes all technical aspect of the music. Using a recurrent neural network, AI-

large success, with AVIA becoming the first AI to be recognised by SACEM, which allows its composition to be protected by copyright infringement. Other AI-powered platforms, such as Jukedeck, are operating as opensource. Therefore, this is the algorithms used in this research. Notably, this algorithm is of high quality, verified by the fact that it has been acquired by ByteDance, the parent company of TikTok (Reuters, 2019). Indeed, there is a growing demand for music creations, with fast pace social media platforms such as TikTok in needs of a cheap, reliable ways of generating high-quality music. Moreover, there are similar demand for fast-paced, low-cost music production for film, game or other types of entertainment that requires music accompaniment. In the last few years, AI-powered platform has made significant progress, allowing it to create personalised music, in which the user can specify the length, speed, mood, key signature, instrumentation and style. It has even allowed users to train the algorithm itself by upload influences soundtracks and create similar music in seconds. Yet, we feel confident that the quality of music synthesized by our algorithm has been of a sufficiently good quality, so this does not place it at an inferior position to the human synthesized music. Still the very design of our study serves to correct for any remaining quality differences. As we ask the respondent to evaluate the same piece of music before and after knowing the nature of its composer, we are able to compare the evaluation of the same piece of music to itself before and after the treatment, thus the difference between music pieces can be captured empirically by music piece specific fixed effects.

Empirical strategy

powered algorithms such as AIVA can understand the patterns and styles of its databases and create its own prediction of the next possible notation. With powerful computational processors, AIVA can continuously test its notation predictions repeatedly across a large database in hours and create its own set of rules to match the style of music. Moreover, using Nvidia GPUs, the company plans to give AIVA the ability to perform plagiarism checks of its creation across large spectrums of existing music (Zulic, 2019).

The methodology included three steps. First, we sought to identify the determinants of the overall valuation of the compositions and establish whether individual cultural tastes play a role in the valuation of the music components. Second, we analyzed the effect of information about cultural proximity (i.e. the nature of the composer) using data on the respondent's re-evaluation of the same samples of music. Third, we established whether the respondent's re-evaluation was consistent with their original valuations of the objective music components.

We began by estimating a reduced form version of model (1) by drawing on the four responses about the perceived value of the four compositions and by assuming their independence, using OLS with robust standard errors. This approach enabled us to analyse the valuation of the compositions without controls for knowledge of the composer, and hence we initially exclude information on cultural proximity, such that:

$$VAI_i = \beta 1 * Taste_i + \beta 2 * Quality\ of\ Creativity_{ij} + e_i \qquad (2)$$

This empirical test aims to establish whether the relative valuations of human-made and AI-made music are affected by the same music components, and this baseline information will help to identify whether objective and rational decisions exist and hence whether human and AI creativity can be substitutes or complements in the creative market.

Using the experimental design embedded in our data collection process, we next assess the valuation performance of the self-declared experts and non-experts before and after the information on the nature of the composer was released. We applied a difference-in-differences approach with the full sample of reported valuations, where the treatment effect is identified as an interaction between the treatment (i.e. the provision of information about the nature of the composer) and the category of composer (i.e. AI- versus human-composed music), such that:

$$diff\_VAI_i = \beta 1{*}Taste_i + \beta 2{*}Quality\ of\ Creativity_{ij} + \beta 3{*}AI + \beta 4{*}After_i + \beta 5{*}AI{*}After_i + e_i \tag{3}$$

The interaction term *AI*After* captures whether the valuation of AI-generated music was evaluated significantly differently when the respondent became aware of the composer-type.

A deeper look at the descriptive statistics suggest that the re-evaluations of whether the respondent liked the music were non-linear, with some respondents increasing, some decreasing and others not changing their reported valuations. Thus, a linear OLS-based difference-in-differences estimation may not capture the effect of the treatment accurately, so we adopt two alternative approaches to expose the true result.

First, model (1) was estimated using separate probit models for each of the groups of respondents who decreased, did not change and increased their valuations respectively, such that:

$$increase\_diff\_VAI_i = \beta_1 Taste_i + \beta_2 Quality\ of\ Creativity_{ij} + \beta_3 AI + e \tag{4}$$

$$no\_diff\_VAI_i = \beta_1 Taste_i + \beta_2 Quality\ of\ Creativity_{ij} + \beta_3 AI + e \tag{5}$$

$$decrease\_diff\_VAI_i = \beta_1 Taste_i + \beta_2 Quality\ of\ Creativity_{ij} + \beta_3 AI + e_i \tag{6}$$

This approach enabled distinct comparisons of the factors that determined increases and decreases in valuations. It also helped to identify whether these reactions were due to cultural proximity and hence whether changes in choice were away from or towards the AI-composer irrespective of whether the respondent's original valuation was favouring or otherwise AI compositions.

Second, a multinomial probit (MNP) model was estimated by operationalizing model (1) using the form:

$$diff\_VAI_i = \beta_1 Taste_i + \beta_2 Quality\ of\ Creativity_{ij} + \beta_3 AI + e_i \qquad (7)$$

In our MNP estimation of model (7), the dependent variable has a value equal to 1 (one) if the respondent's valuation decreased after the provision of information regarding the AI-composer, a value equal to 2 (two) if there was no change in this valuation, and a value of 3 (three) if there was an increase in the valuation of the composition after receiving information that the music was composed by an AI. This approach allows us to consider the joint probabilities between the three different groups of responses to the treatment.

Finally, we focused only on the composition re-evaluations using the unbiased original evaluations of the quality of the creative product as determinants as used in model (2), such that:

$$reranked\_VAI_i = \beta_1 Taste_i + \beta_2 Quality\ of\ Creativity_{ij} + e_i \qquad (8)$$

This final approach enables us to identify three concerns. First, it enables us to identify which components of taste and quality contributed more to the triggering of cultural proximity bias in the utility functions. Second, it allows us to identify whether people exhibited stronger reactions to AI-generated compositions or whether the cultural proximity effect appears in the valuation of both human and AI compositions. Third, it helps us to distinguish between two things: (i) whether the respondent's re-evaluation was entirely an emotional fast thinking bias towards the human producer and unrelated to the objective analytical valuations of the composition or (ii) whether the re-evaluation was a deep reflection and an upgrade of the respondent's valuation and an unbiased perception of quality.

5. Results

Our study assesses whether there is a cultural proximity bias in musical composition utility functions, and to cultural goods more generally. The regression results presented in table 1 illustrate that individual tastes do play a role in assessments of the quality of music compositions, but tastes respond asymmetrically to different types of musical compositions. Preference for classical compositions predict a higher preference for piano compositions, which were the instrument of choice in samples 1 and 2. Individual tastes for pop and electronic music, being male and younger all predict greater preference for samples 3 and 4, which were dance music compositions. These results suggest that people do not have significantly different utility functions but rather that different types of creative products trigger different components of a universal utility function.

Music characteristics were consistently important factors that shape people's preference for particular compositions, and this result is consistent across all types of music although rhythm seems to have the lowest level of importance in determining the compositions value. These results demonstrate that objective and quantifiable product characteristics are distinctly different from the subjective qualitative aspect of music. Subjective aspects of music trigger a uniform valuation response across different types of music, while objective product characteristics trigger different types of personal tastes (such as towards a solo pianist (as music samples 1 and 2) or dance music (as in samples 3 and 4)).[16]

Our main interest in these estimations was whether indifference between the valuations of AI- relative to human-generated compositions elicits any difference in the utility of the two products. The results point to a slightly higher importance of individual tastes that are exhibited when evaluating human compositions (samples 1 and 3) while AI-compositions seem to be preferred for objective quantifiable characteristics reasons. However, self-declared musical experts seem to dislike significantly the AI composition (sample 4) even after controlling for its objective characteristics (melody, harmony, etc.). These results indicate that AI-compositions seem unable to address important qualitative and emotional needs in the consumer's utility function even when the respondent is not aware that the product has been generated by an AI. This evidence suggests that AI and humans are complements, and that AI could boost the technical side of the creative process, although AI is not a full substitute due to the appeal of human creativity.

{Table 1}

The second step in this study explores the effect of cultural proximity on the operation of the utility function. Initially, we used a standard difference-in-differences approach, where we have two groups (AI- and human-composed music) and a treatment (providing the information about the nature of the music: AI- versus human-composed music). The effect

[16] We cross-checked whether the self-reported utility levels consistently transformed into extrinsic preference. We test this in two ways: (i) through a Probit model where the dependent variable is a dummy variable that is equal to 1 when the person purported to prefer the human version of the solo piano music or the human version of the band disco music. We explored the respondent's individual tastes and the reported evaluation they gave to the music characteristics for the two compared samples; (ii) we directly regress the preference for the human composition over the AI composition on the reported preference for the two compared samples. These results are presented in Appendix 2. The self-reported utility of the respondents seems consistently transferred into extrinsic preferences when the person is unaware of the nature of the composer.

was explored first using OLS via the interaction between the AI-group and the information about the nature of the AI, as in model (3). However, we identified from the descriptive statistics the presence of clear non-linearities in the effect of the treatment on the change in the valuation of the music (model (3)), and hence we split the reactions to the treatment into three distinct linear responses (increases, no change and decreases) and assessed each group of responses separately in a probit model in order to determine what characteristics drove the particular type of response. These results are presented in tables 2 and 3 with table 2 revealing the results from the OLS and probit estimations and table 3 presenting the proportions of the three responses to the AI-related information.

{Tables 2 & 3}

The difference-in-differences estimations, shown in table 2, reveal that the treatment effect of informing the respondents on the nature of composer has a statistically significant and positive effect on the evaluation of human-generated music relative to music generated by the AI. However, the interaction effect between the two variables suggests that the treatment effect is not statistically significant, and so we are unable to present evidence which implies that the provision of information on the nature of the composer leads to a systematic decrease in the evaluation of the samples; nevertheless it is clear that the AI-compositions received more frequent inferior evaluations, which suggests that respondents on average adjusted their responses in favour of the human composers when re-evaluating the compositions. This conclusion strengthens through inspection of the probit marginal effects estimates. As shown in table 2 columns 2 – 4, AI compositions experienced clear falls in evaluations due to the treatment, there was no change in preferences towards AI when the evaluations were driven only by individual tastes, and the increase in evaluations were clearly in favour of human-generated compositions, thereby eliciting a significant negative effect of the treatment towards AI compositions. Hence, evaluation adjustments in response to knowledge of the nature of the composer were consistently in favour of the human composer and against the AI composer.

To add precision to the results based on our probit estimations, we estimated a multinomial probit, and the corresponding results are presented in table 4 below. These results confirm our previous findings in two ways. First, the importance of the cultural proximity of being human is confirmed, as the respondents react to the treatment information by decreasing their evaluation of AI composed music and/or by increasing their evaluation of the human composed music. Those who decreased their evaluations of AI music less likely to be people with preferences for pop or electronic music, and such individuals were more likely to increase their evaluation in favour of human compositions. This is a particularly intriguing results because pop and electronic music could be interpreted as having a qualitative distinction between more human- and AI-generated music.

{Table 4}

Fans of pop and electronic music were more responsive to the information treatment than the aficionados of the classical music. We interacted these types of tastes with the AI dummy variable in order to understand whether the response of the two different types of music was in two different directions. The interactions were not significant, indicating that the two personal types were both equally responsive to the treatment and did not differ in terms of perceiving AI as a substitute. Instead, both pop and classical music fans exhibited sensitivity to the cultural proximity of the composition.[17] We interpret these results as evidence in favour of the claim that while tastes for complementarity may differ between consumers, they do exhibit a general cultural proximity towards human compositions. This raises important questions as to whether the market will adapt its taste to the supply of AI-generated creative products or whether there will be a significant backlash from consuming non-diffused entirely AI-generated products.

Finally, in a third step we explore how the determinants of the initial valuation of the music (reported before the release of the nature of the composer) relates to the change in the ranked of the valuation once the nature of the composer was released to the respondents (with samples 2 and 4 being generated by the AI). These results are shown in table 5 and most of these specifications reveal an inferior level of importance of personal tastes and instead changes in the rankings seem to be in response to the characteristics of the music. Initially the lack of information on the nature of the composer resulted in neutral valuations of the samples of music as comparable units of musical creativity, but in the re-ranked evaluations (after the respondents were informed about the AI nature of sample 2 and 4) the respondents clearly gave more weights to the more filigree characteristics of the music and the importance of the overall presentation decreased. We interpret this as a desire to support the more culturally proximate human-composer with people trying to think more analytically rather than following their emotions and hence intentionally seeking justification to support human composers. This illustrates how people might be driven initially by fast thinking and respond more to their overall perception, but their natural cultural proximity to the human composers is not a bias but a natural need for humanness which is ingrained in their culturally learned analytical valuation of the world. People do have a desire to prefer human nature and when

[17] These results are not entirely surprising since it is known that in the electronic music world a practice known as 'humanizing' of the electronic sound is being introduced to make the music more appealing and responding to the needs of the consumer. There is even a 2010 US patent for humanizing electronic music (Patent No.: US 7,777,123 B2, under the name of Hunnig *et al.*)

they think analytically they can identify whether a product matches what human nature is supposed to be and reflected in our learned categorization and qualification of music creativity. In the particular case under analysis, people sought and behaved as if the provision of information enabled them to identify more successfully the exact match between their analytical reasoning about music and their cultural bias towards human made creativity.

{Table 5}

6. Discussion

The current study has a generalizable key message for businesses to adjust their expectation to the realistic rates of acceptance and adoption that the Ai technology is likely to have. AI-produced goods and services may as well become better performing than human-made ones. Yet, the results of our study suggest that besides objective characteristics, what will play a key role in the customers willingness to adopt and pay for AI goods and services is clearly not only the objective characteristic of the good or service but also the taste for the importance of the human nature of the work embodied in the produced good or service. Economics would classify such a behaviour as discrimination (Arrow 1972, Becker 1957, Baert and De Pauw 2014; Busetta, et al. 2018).

In specific, in Gary Becker's (1957) sense, one type of discrimination is the discrimination driven by a subjective taste in favour (or against) a particular identity, which is expressed by the higher (or lower) willingness of the customer to pay for an identical good or service when it is associated with this identity (see Becker 1957: pp. 13-16). Thus, the results of our study can be understood as the customers willingness to negatively discriminate against the AI products based on the taste to associate some importance related to the condition of the producer being a human.

We are able to create unique experimental conditions for capturing this taste for discrimination driven by the importance of being human by keeping the objective characteristics of the good evaluated fixed and triggering changes in the taste component by providing additional information about the AI nature of the composer. Since the experiment in-built in our survey design entails evaluating one and the same music entity twice – the two evaluations differ only by the additional information about the AI nature of the composer and any difference between the two evaluations (self-reported utilities) is clearly driven by the taste for AI versus human identity. A difference in the self-reported utility cannot be driven by objective characteristics, as they remain the same, hence the taste for being human is what can only explain the difference in self-reported utility. Meanwhile self-reported utility is deeply related with willingness to pay and it is known that the latter can be derived from the former (see for instance McFadden (2012).

Lower willingness to pay for a product because of its AI-nature implies that business expectations and plans based solely on the objective characteristics of the AI-product or service will lead businesses to overestimate the expected returns from their AI-related investments. Further, case-based research will be necessary for establishing what is the degree of taste for discrimination against the AI-nature for every particular market. Again in line with Becker (1957, p. 17; 75-77), it will be then necessary to estimate the ratio between the improvement of characteristics (in terms of substitution between AI and human) and the magnitude of affect bestowed by the customers to the taste for importance of being human for the particular market. That will allow to arrive at a realistic estimation how the market will actually respond to the AI-product or service and how much the customers will be willing to pay for the latter.

7. Conclusion

Creativity is the ability to recombine ideas, and since artificial intelligence can generate much more numerous recombinations than the human brain in an identical period of time, so AI is more efficient in generating a creative output from an economic efficiency point of view. However, creative goods and services also contain cultural value, which relates to human emotions, morality, experiences, etc., and AI products do not involve a human component in their creation, and therefore lack the cultural value of being associated with humanness. What remains unclear in the literature is whether consumers differentiate between creative goods that have been generated by AI and humans depending on the perception of cultural value. To fill this gap in the literature, this study examined consumers' perceptions towards creative products, specifically music compositions, before and after respondents become aware that the creative good was produced by a human or an AI.

The study identified two pathways in which the utility function seems to reveal the propensity towards what is a human-generated product and away from an AI-made product, and these are both associated with cultural proximity. First, our results illustrate that there is a genuine desire to readjust the reported satisfaction with a creative product away from an AI-made produce in favour of a human-made alternative. Second, this re-evaluation seems to rely on deep analytical thinking since it leads to a significant unbiased improvement in the reported perception of the overall quality of the human-made creative product. The latter indicates that even if AI is more economically productive and efficient, since AI remains unable to fully substitute for humanness, so over-optimistic manufacturers' investments in AI-based production may face a severe unexpected lack of demand for creative goods.

Our findings confirm the claims of Fry and Osborn (2017) of a lack of substitutability of humans with AI in the creative sector. However, unlike previous studies on the matter, we do not base our findings on respondent's predictions but rather on the psychological mechanisms and comparison between characteristics of seemingly substitutable products generated by AI and humans. It is consistent with Turner and Lourenço (2012), who found that cultural proximity matters in the context of creative products, and Monier (2018), who identified that cultural proximity, and specifically social capital, governs even moral acts of philanthropy. Thus, our findings contend that cultural proximity is conflated with consumers' sense for the value of 'humanness' and the interaction of these two factors matters in consumers' utility function relating to AI- and human-produced goods.

The results illustrate that people show preference for human products over AI products due to cultural proximity with the humanness. This however does not guarantee that human-generated products will not be substituted by AI-generated alternatives in the creative sector, as it illustrates that at this point in time the AI technology has not become a full substitute for the human factor for production. Our results do indicate that people would defend the humanness, since there appear no objective reason for the change in rankings revealed in this study; people may continue to defend the humanness when they are informed that a product is not of human nature. AI technology has the potential to be diffused invisibly in other products and may increasingly penetrate human life without triggering the cultural proximity preference.

Further research should consider resampling of the population, greater analysis of the differences between treated and non-treated groups, and examine the cultural proximity reaction to AI in different geographical contexts. Further disentangling of the cultural proximity mechanism and greater understanding of the cause(s) of the objective lack of humanness in the AI-generated product could enable the use of neuro-economics approaches to respond to consumption asymmetries across the human-AI ratio continuum.

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