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# Can Indian Listeners Distinguish Between Artificial Intelligence and Human generated music?

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***Abstract***
*Purpose: This research paper aims to find out the level of awareness about and attitude towards AI-generated music among listeners in the Indian state of Gujarat. It also attempts to check if listeners can distinguish between music generated by AI and by humans.*
*Design/methodology/approach: The paper uses a questionnaire survey of 150 listeners administered electronically to achieve its goals.*
*Findings: This study found that the attitude of music listeners in India towards music generated by AI is moderately favorable. The most positive attitude is found towards free downloading and streaming of music generated by AI while the least positive is towards purchasing AI-generated music. A high percentage of respondents were willing to recommend AI generated music to their friends.*
*There is a clear expectation that record labels should openly/clearly inform if songs or albums were written by AI and that AI composed music should be cheaper. Listeners in India also believe that music's value will decrease in society if it is composed by AI and that Professional musicians should not use AI for composing their music.*
*In terms of distinguishing between music created by AI and humans, preferences, in each piece of music given to the listeners, 51 percent respondents were able to clearly identify whether it was created by AI or by humans.*
*Practical implications: The findings of this study can help creators of AI-generated music understand the importance of creating awareness about such music. It will also help them in developing strategies for encouraging purchase, download and streaming of AI-generated music.*
*Originality/value: The findings of this study make several contributions to the existing literature on AI-generated music. First, it offers insight into the level of awareness about AI-generated music, the attitudes of Indian listeners towards such music and their preferences for purchasing, downloading or streaming such music. Secondly, this study also shows whether regular music listeners are able to distinguish between AI and human generated music.*
***Key words:*** *artificial intelligence, music, AI music, India, attitude*

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## I. Introduction

AI generally refers to efforts to build computers able to per- form actions that would otherwise require human intelligence, such as reasoning and decision-making. It denotes a fundamental shift, from humans telling computers how to act to computers learning how to act. AI does this largely through machine learning, including 'deep learning' techniques (Franke, 2019).

Computational creativity is the study of building software that exhibits behavior that would be deemed creative in humans. Such creative software can be used for autonomous creative tasks, such as inventing mathematical theories, writing poems, painting pictures, and composing music. However, computational creativity studies also enable us to understand human creativity and to produce programs for creative people to use, where the software acts as a creative collaborator rather than a mere tool.

Music composition, understood as generating new music from rules (Delgado et al., 2009), has been the object of study and application in Computer Science and Artificial Intelligence (AI) during the last decades. Within this scope, some systems based on AI techniques have appeared to support the composition process. They include LISP programming (Taube, 1991), Case-based reasoning (Ribeiro et al., 2001), Genetic Algorithms (Moroni et al., 2000), restrictions (Henz et al., 1996; Anders et al., 2005), or ontologies and cognitive modeling (Alvaro et al., 2006).

Because of the fact that exploration of AI in the music industry has started recently on a large scale, there is some research regarding the attitudes and perceptions of listeners towards music created by AI and the humanization of music created by AI (Schubert et al., 2017).

Some recent, but limited evidence suggests that the typical listener is no longer able to distinguish between an algorithm and a human performance. Deep blue as a chess player attracted much media attention in the mid-1990s. However, the arguably much more difficult and controversial area of computational simulation of artistic expression may well have been solved, yet passed more-or-less unnoticed. Here the algorithm, like the human, aims to give the impression of creativity through the artistic manipulation of parameters concerned with performance, as distinct from the composition itself (Quinto, Thompson, & Taylor, 2014; Schubert & Fabian, 2014). The RENCON contest itself has not shown that human performances can be matched by computational algorithms, since the aim of the competition is to determine the success of an algorithm with respect to other algorithms. The matter of comparison with human performance has received attention, particularly in terms of the so-called musical Turing test (Hiraga et al., 2004; Katayose et al., 2012).

In the Indian context, a Pune-based academician has designed a software, which can generate 'bandish' of ragas in Indian classical music using AI. that can code the concepts and composition rules of Indian classical music to generate a 'bandish' (composition) every time the vadi (dominant) and samvadi (sub dominant) swaras are provided as inputs. This can be considered the first step towards using AI in the Indian music scene ("New software can compose Indian classical music with help from AI", 2020)

Further research in the Indian context regarding the attitude of listeners towards music generated by AI is important. Therefore, this study aims to explore the perceptions of listeners about AI generated music among listeners in Gujarat, India. More specifically, the study addresses the following research questions:

*RQ1: Is there an awareness about AI-generated music among listeners in the Indian state of Gujarat?*
*RQ2. What are the attitudes of listeners in the Indian state of Gujarat towards music generated by AI?*
*RQ3: Can Indian listeners differentiate between music generated by AI and by humans?*

The paper is organized as follows. The next section deals with an in-depth literature review about the use of artificial intelligence in the arts and especially in music world-wide. The next section discusses the research methodology adopted. This is followed by the findings of the survey conducted among music listeners in the Indian state of Gujarat. The conclusions from the findings are presented next. Finally, the discussion section provides the practical implications of the study, limitations and further scope for research.

## II. Literature Review

*Meaning and Evolution of Artificial Intelligence*

Artificial Intelligence (AI) is now considered as a classical discipline of computer science. AI generally refers to efforts to build computers able to perform actions that would otherwise require human intelligence, such as reasoning and decision-making (Mainzer, 1998). It denotes a fundamental shift, from humans telling computers how to act to computers learning how to act. AI does this largely through machine learning, including ‘deep learning’ techniques (Mainzer, 1998)

AI systems have been defined as ‘self-training structures of Machine Learning predictors that automate and accelerate human tasks’. In turn Machine Learning (ML) is ‘the field that thinks about how to automatically build robust predictions from complex data’ (Taddy, 2018).

“Artificial Intelligence (AI) is the part of computer science concerned with designing intelligent computer systems that exhibit the characteristics we associate with intelligence in human behaviour—understanding language, learning, reasoning, solving problems, and so on” (Barr & Feigenbaum, 1981). Since 1956, the development of technology has rapidly grown. Today, in the 21st century, AI is all around us. In the 63 years since AI was officially born, it has been used in a variety of fields, some of which are: finance, marketing, healthcare, medical diagnosis, robotics, automation, optical character recognition, nonlinear control, semantic webs, education, transportation, music, artificial life, game theory, computational creativity, speech recognition, bio-inspired computing, face recognition, hybrid intelligent system, etc. (Zulić, 2019).

The idea of intelligent machines arose in the early 20th century. From the beginning, the idea of ‘human-like’ intelligence was key. Following Vannevar Bush’s seminal work from 1945, where he proposed “a system which amplifies people’s own knowledge and understanding”, Alan Turing asked “Can a machine think?” In his famous 1950 imitation game, Turing proposed a test of a machine’s ability to exhibit intelligent behaviour equivalent to that of a human (Petropoulos, 2018).

ML emerged in the 1970s in response to the failure of rule-based approaches where human experts hard-coded knowledge in Artificial Intelligence systems (Markoff, 2015). ML’s approach is to instead develop algorithms that can recognize patterns in labeled data with less need for human intervention and use the resulting models to make predictions about new observations. Economic analyses of AI focus on its ability to reduce the costs of prediction, an important task in many industries (Agrawal et al., 2018).

Existing literature differentiates between weak and strong AI. Weak or narrow AI focusses only on specific pre-learned reasoning or problem-solving tasks, such as playing chess or translating languages. On the other, strong AI, sometimes also termed full AI or general intelligent action, aims at achieving or surpassing human levels in “reasoning, knowledge representation, planning, learning, natural language processing, perception and the ability to move and manipulate objects." (Artificial Intelligence, 2021). Here, the long-term goal is artificial general intelligence, which is defined as a "hypothetical intelligence of a computer program that has the capacity to understand or learn any intellectual task that a human being can" (Artificial General Intelligence, 2021). Therefore, it is the strong AI that is relevant for the present discussion; and particularly this is currently making enormous progress with the developments of so-called artificial neural networks, its variant the convolutional neural networks, deep learning, deep neural networks and reinforcement learning networks (van der Maas et al., 2021).

Artificial intelligence (AI) is changing the economy: it is impacting on the way we shop, on the way we communicate, on the way we do research. AI is, in short, set to be nothing less than "vital to everything". Indeed, it is difficult to think of areas that AI cannot speed up, improve, or otherwise change (Franke, 2019). AI generally refers to efforts to build computers able to perform actions that would otherwise require human intelligence, such as reasoning and decision-making. It denotes a fundamental shift, from humans telling computers how to act to computers learning how to act. AI does this largely through machine learning, including 'deep learning' techniques. The field is currently enjoying an "AI spring", with AI development accelerating significantly over recent years. A 2017 report estimated that 90 percent of the world's data had been created within the preceding five years. The same period saw a fifteen-fold growth in the number of developers of graphics processing units (GPUs) – hardware crucial for AI. Together, these developments have led to a significant increase in AI research around the world, resulting in better algorithms becoming more widely available. This, in turn, has generated more research. AI's potential can appear almost limitless. AI applications already have significant economic and social benefits. In the health sector, AI is used to read scans and improve the accuracy of diagnoses. In agriculture, AI can help improve crop yields. Factories, server farms, and other energy-hungry businesses use AI to become more efficient in their energy consumption. According to Goldman Sachs, there is "potential for AI and machine learning to re- shuffle the competitive order across every industry" (Franke, 2019, p. 4)

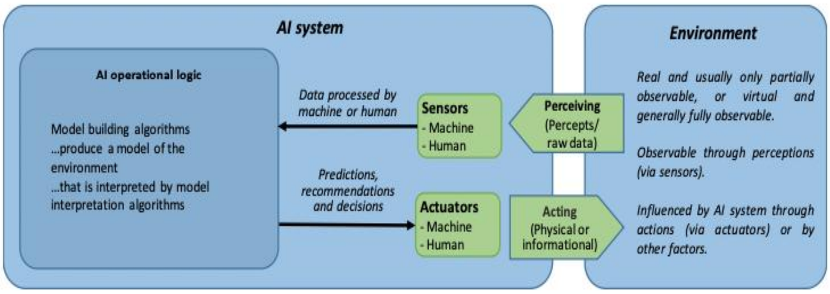
AI is reshaping economies, promising to generate productivity gains, improve efficiency and lower costs. It contributes to better lives and helps people make better predictions and more informed decisions. There is no universally accepted definition of AI. In November 2018, the AI Group of Experts at the OECD (AIGO) set up a subgroup to develop a description of an AI system. The description aims to be understandable, technically accurate, technology-neutral and applicable to short- and long-term time horizons. It is broad enough to encompass many of the definitions of AI commonly used by the scientific, business and policy communities. As well, it informed the development of the OECD Recommendation of the Council on Artificial Intelligence (OECD, 2019).

*Conceptual view of an AI system*

The present description of an AI system is based on the conceptual view of AI detailed in Artificial Intelligence: A Modern Approach (Russel & Norvig, 2009). This view is consistent with a widely used definition of AI as "the study of the computations that make it possible to perceive, reason, and act" (Winston, 1992) and with similar general definitions (Gringsjord & Govindarajulu, 2018).

A conceptual view of AI is first presented as the high-level structure of a generic AI system (also referred to as "intelligent agent") (Figure 1). An AI system consists of three main elements: sensors, operational logic and actuators. Sensors collect raw data from the environment, while actuators act to change the state of the environment. The key power of an AI system resides in its operational logic. For a given set of objectives and based on input data from sensors, the operational logic provides output for the actuators. These take the form of recommendations, predictions or decisions that can influence the state of the environment.

*Figure 1: Conceptual View of Artificial Intelligence System*




*Source*: As defined and approved by AIGO in February 2019.

Research has historically distinguished symbolic AI from statistical AI. Symbolic AI uses logical representations to deduce a conclusion from a set of constraints. It requires that researchers build detailed and human-understandable decision structures to translate real- world complexity and help machines arrive at human-like decisions. Symbolic AI is still in widespread use, e.g. for optimization and planning tools. Statistical AI, whereby machines induce a trend from a set of patterns, has seen increasing uptake recently. A number of applications combine symbolic and statistical approaches. Combining models built on both data and human expertise is viewed as promising to help address the limitations of both approaches. AI systems increasingly use ML. This is a set of techniques to allow machines to learn in an automated manner through patterns and inferences rather than through explicit instructions from a human. ML approaches often teach machines to reach an outcome by showing them many examples of correct outcomes. However, they can also define a set of rules and let the machine learn by trial and error. ML is usually used in building or adjusting a model, but can also be used to interpret a model's results. ML contains numerous techniques that have been used by economists, researchers and technologists for decades. These range from linear and logistic regressions, decision trees and principle component analysis to deep neural networks. The real technology behind the current wave of ML applications is a sophisticated statistical modelling technique called "neural networks". This technique is accompanied by growing computational power and the availability of massive datasets ("big data"). Neural networks involve repeatedly interconnecting thousands or millions of simple transformations into a larger statistical machine that can learn sophisticated relationships between inputs and outputs. In other words, neural networks modify their own code to find and optimize links between inputs and outputs. Finally, deep learning is a phrase that refers to particularly large neural networks; there is no defined threshold as to when a neural net becomes "deep" (OECD, 2019).

*Machine Learning*

Machine learning enables computer programs to acquire knowledge and skills, and even improve their own performance. Big data provides the raw material for machine learning, and offers examples that computer programs can use for 'practise' in order to learn, exercise and ultimately perform their assigned tasks more efficiently. In principle, machine learning follows Turing's recommendation of teaching a machine to perform specific tasks as if it were a child. By building a machine with sufficient computational resources, offering training examples from real world data and by designing specific algorithms and tools that define a learning process, rather than specific data manipulations, machines can improve their performance through learning by doing, inferring patterns and checking hypotheses. At the core of this learning process are artificial neural networks, inspired by the networks of neurons in the human brain. The goal of the neural network is to solve problems in the same way that a hypothesised human brain would, albeit without any 'conscious' codified awareness of the rules and patterns that have been inferred from the data. Modern neural network projects typically work with a few thousand to a few million neural units and millions of connections. They are called deep because of the multiple intermediate hidden layers they have. However, deep neural networks are still several orders of magnitude less complex than the human brain and closer to the computing power of a worm. Deep neural networks have proven very effective. There are several examples of games and competitions in which machines can now beat humans (Petropoulos, 2018). By now, machines have topped the best humans at most games traditionally held up as measures of human intellect, including chess (recall for example the 1997 game between IBM's Deep Blue and the champion Garry Kasparov), Scrabble, Othello and Jeopardy! However, many of these machines are programmed to perform specific tasks, narrowing the scope of their operation. Humans remain superior in performing general tasks and using experience acquired in one task to deliver another. (Petropoulos, 2018)

AI is supposed to simulate human intelligence in order to support or even extend humans' abilities (Otte, 2019). There are processes like pattern recognition in huge data sets, massive data-mining in various forms of machine learning where AIs already presently outperform humans by far. On the other hand, there are cognitive processes that we usually subsume in the construct of intelligence and that are included in many current intelligence tests, where AIs fail miserably (Neubauer, 2021).

*Use of AI in Creative Fields Including Music*

Artificial Intelligence (AI) research has traditionally focused on exploring and modeling the left-brain side of human intelligence: science, math, logic, engineering, etc. However, its applications are not limited to left-brain functions and have crossed over in several creative fields.

Some noteworthy examples are a non-photorealistic rendering algorithm able to convert photographs into impasto-style images (J. P. Collomosse and P. M. Hall); ArtiE-Fract, an interactive evolutionary art tool (Evelyne Lutton); autonomous biology-inspired approaches for the evolution of images with aesthetic proprieties (Gary Greenfield); Aesthetiscope, a generative art system that creates abstract color grids based on input text (Hugo Liu and Pattie Maes); a machine-learning approach to create and explain expressive musical performances (Rafael Ramirez and Amaury Hazan); Sören Tjagvad Madsen and Gerhard Widmer (2006) research on the understanding of piano performances; Judy A. Franklin (2005) research on Long Short-Term Memory (LSTM) recurrent artificial networks to learn and generate new musical pieces, to name a few.

Computational creativity is the study of building software that exhibits behavior that would be deemed creative in humans. Such creative software can be used for autonomous creative tasks, such as inventing mathematical theories, writing poems, painting pictures, and composing music. However, computational creativity studies also enable us to understand human creativity and to produce programs for creative people to use, where the software acts as a creative collaborator rather than a mere tool (Mántaras, 2017)

There is an ongoing debate about if or to what extent AI methods are creative. According to Boden (2004), there are three types of creativity: (i) explorational, (ii) transformational, and (iii) combinational. Certain AI methods potentially allow the exploration of musical styles, the transformation of rules for achieving novel musical results, and the combination of conceptual spaces for forming altogether new ones. There is, however, still debate on whether the creativity of such systems, some of which can arguably be categorized to one of the aforementioned creativity categories, is a reflection of the human agent’s creativity (Kaliakatsos-Papakostas et al., 2020).

The process of creativity needs to be understood as a new way of behaving, which would include a piece of software (or one of its parts) that goes beyond the physical details of the program (Colton et al. 2014, 5). Since the origination of the first programs capable of composing music, no artificial intelligence system that composes music has become a part of the broader community of music, but now, in the 21st century, this is changing. With the rapid development of technology, artificial intelligence has enabled a faster flow of information, and thus faster ways of solving the problems we face in the digital world. Thus, the possibilities for developing newly advanced composer- software are much greater, as are the possibilities of its dissemination within the digital world (Zulić, 2019).

Research documents an increasing use of artificial intelligence in the field of music, also sometimes referred to as computer music. Computer Music (CM) is an inter-disciplinary domain where Psychology, Acoustics, Engineering, Computing and Music meet (Moore, 1990). Computer music composition focuses on those aspects related to music composition and the use of Information Technologies (IT). Music composers receive assistance from computers for various functions such as score notation, sound synthesis, algorithmic composition and experimentation on Artificial Intelligence (AI) applied to music.

With recent development such as cloud computing technologies, composers now have even more creative possibilities to explore (Li et al., 2011).

One of the earliest developments in modeling music composition processes and music representation was the EvOntology (Alvaro et al., 2006), an in-depth study of the knowledge level (Newell, 1982) for music composition, which served as the basis for developing EvMusic (Alvaro et al., 2005), a productive composition environment written in Lisp programming language as a stand-alone application. Later on, a remote graphic user interface was developed and published on the Web in a client-server approach which was the first step towards a distributed version. The representation MusicJSON (Alvaro and Barros, 2010) was designed as a shared musical representation to take advantage of cloud computing for different musical technologies to efficiently coexist in the same system. Alvaro and Barros (2011 and 2010) conducted several experiments on the integration of musical services and their application to real musical composition. Music composition, understood as generating new music from rules (Delgado et al., 2009), has been the object of study and application in Computer Science and Artificial Intelligence (AI) during the last decades. Some of the systems based on AI techniques that have been developed so far to support the music composition process are LISP programming (Taube, 1991), Case-based reasoning (Ribeiro et al., 2001), Genetic Algorithms (Moroni et al., 2000), restrictions (Henz et al., 1996; Anders et al., 2005), or ontologies and cognitive modeling (Alvaro et al., 2006).

The advent of cloud-computing architectures created a new paradigm in which computer infrastructure and software are provided as a service (Ambrust et al., 2009), referred to as Software as a Service (SaaS). Every day new applications appear in the Web, in the form of SaaS, providing the user with the capability of ‘‘working in the cloud’’, on which the information is no longer stored in local hard disks but in Web servers. Computation infrastructure is also offered as a service (IaaS), thus enabling the user to run the customer software (Alvaro & Barros, 2013).

The earliest connection between artificial intelligence and music began in the mid-1960s, which focused on music as a cognitive process or as a set of activities modelled with the aid of computer programs (Berz and Bowman 1995). The first published paper on algorithmic music composition described the process of music composition using the Ural-1 computer (Zaripov, 1960). Another significant discovery was the Ray Kurzweil computer that was programmed to compose music (Kurzweil Technologies n.d.). Years after this program was created many additional discoveries were made using artificial intelligence including: “intelligent instruments; deeper, multifaceted representations for scores and sounds; intelligent musical data bases; singing and talking input with singing and talking output; a better understanding of human musical cognition and musical universals; new musical machines with capabilities beyond those of a single performer; more intelligent sound-analysis systems; performance systems capable of intelligent response to musical sound; and new and interesting compositional rule structures," (Roads 1980, 23).

Many diverse artificial intelligences (AI) methods have been proposed for music generation over many decades. From the rule-based and Markov approaches of the Illiac Suite (Hiller and Isaacson, 1979) to more recent deep learning approaches that allow interactive piano performance tools (Donahue et al., 2019) and score filling (Huang et al., 2019a), researchers find it intriguing to test AI methodologies for music generation. Among the many reasons that the application of AI for generating music is interesting and important, we find the fact that music is organized on many levels of abstraction, where even complex rules may not be enough to capture deeper structures.

Rothgeb (1969) wrote a SNOBOL program to solve the problem of harmonizing the unfigured bass (given a sequence of bass notes infer the chords and voice leadings that accompany those bass notes) by means of a set of rules such as: "If the bass of a triad descends a semitone, then the next bass note has a sixth." The main goal of Rothgeb was not the automatic harmonization itself but to test the computational soundness of two bass harmonization theories from the eighteenth century. This could be considered one of the first attempts at using computers for music composition.

Moorer (1972) program on tonal melody generation generated simple melodies, along with the underlying harmonic progressions, with simple internal repetition patterns of notes. This approach relies on simulating human composition processes using heuristic techniques.

Later, Ebcioglu (1993) developed an expert system, CHORAL, to harmonize chorales in the style of J. S. Bach using a logic programming language designed by the author. CHORAL is given a melody and produces the corresponding harmonization using heuristic rules and constraints.

Another program MUSACT (Bharucha, 1993) uses neural networks to learn a model of musical harmony. It was designed to capture musical intuitions of harmonic qualities. In HARMONET (Feulner, 1993), the harmonization problem is approached using a combination of neural networks and constraint satisfaction techniques. The neural network learns what is known as harmonic functionality of the chords (chords can play the function. of tonic, dominant, subdominant, etc.) and constraints are used to fill the inner voices of the chords. MELONET (Hörnel and Degenhardt, 1997; Hörnel and Menzel, 1998) uses a neural network to learn and reproduce a higher-level structure in melodic sequences. Given a melody, the system invents a Baroque-style harmonization and variation of any chorale voice. Pachet and Roy (1998) also used constraint satisfaction techniques for harmonization. These techniques exploit the fact that both the melody and the harmonization knowledge impose constraints on the possible chords. Efficiency is, however, a problem with purely constraint satisfaction approaches.

Morales-Manzanares et al. (2001) developed a system called SICIB capable of composing music using body movements. This system uses data from sensors attached to the dancer and applies inference rules to couple the gestures with the music in real time. One of the best-known work on computer composition using AI is David Cope's EMI project (Cope, 1987; Cope, 1990). This work focuses on the emulation of styles of various composers. It has successfully composed music in the styles of Cope, Mozart, Palestrina, Albinoni, Brahms, Debussy, Bach, Rachmaninoff, Chopin, Stravinsky, and Bartok. It works by searching for recurrent patterns in several (at least two) works of a given composer.

One of the most recent developments in this area is Artificial Intelligence Virtual Artist or AIVA, "an AI capable of composing emotional soundtracks for films, video games, commercials and any type of entertainment content". AIVA uses a process quite different from the process followed by human composers. It uses deep neural networks to look for patterns and rules in compositions and uses this information to learn the basics of style and music (Aiva Technologies 2017).

*Challenges in Humanizing Music Generated by AI*

Most machine learning techniques extract the information from a number of examples in order to create their models, which are measured based on the notion of entropy or unpredictability (Shannon, 1951) and are used to create new music pieces. Conklin and Witten (1995) state that the main disadvantages of stochastic processes are that the probabilities need to be discovered by analyzing many pieces, which is essential if we want to simulate one style. Second, it is difficult to capture higher or more abstract levels of music because it has several deviations from the norm.

Additionally, most AI systems are knowledge-based systems (KBS) which are symbolic and use rules or constraints. Even though KBS seem to be the most suitable choice for music when we try to model well defined domains or we want to introduce explicit structures or rules, there are several challenges faced when they are used for algorithmic composition. First of all, knowledge elicitation is difficult and time consuming, especially in subjective domains such as music. Since KBS act as they are programmed to, they are dependent on the ability of the "expert", who in many cases is not the same as the programmer. Adding all the "exceptions to the rule" and their preconditions, which is necessary in a field such as music, overcomplicates the system. (Papadopoulos & Wiggins, 1999)

KBS can be classified on the basis of their method of storage of information, into subsymbolic/distributive (Artificial Neural Networks, ANN) and symbolic (Machine Learning, ML). ANNs have been used extensively in the last years for musical applications (Todd and Loy, 1991; Leman, 1992; Griffith and Todd, 1997), and have been relatively successful, especially in domains such as perception and cognition. Todd (1989) used a feed-forward ANN with feedback for melody generation. Mozer (1994) generated melodies using ANNs which "suffer from a lack of global coherence". Bellgard and Tsang (1994) constructed an effective Boltzmann machine (EBM) for harmonization. Melo (1998) used two cooperative ANNs operating on different levels in an attempt to capture harmonic tension in music. The ANNs were trained based on the mediant of the tension curve reported by 10 listeners who were asked to listen to the last movement of Prokovief's 1st Symphony and to indicate their estimation of dynamic musical tension by pushing a sprung wheel. The ANNs could predict quite well the tension of an unseen part of the piece (80% was used as training data) and could also generate music, based on a given tension curve, but not as successfully.

ML implementations are not very common. Widmer (1992) used ML for the harmonization of melodies (Ponsford et al., 1999) derived a probabilistic grammar capturing the harmonic movement of a corpus of seventeenth-century dance music. Schwanauer (1993) used five learning techniques, learning by rote, learning from instruction, learning from failure, learning from examples, learning by analogy and learning from discovery for the implementation of a system (MUSE) which could accomplish different harmonization tasks, from the simpler, completing the inner voices for a given soprano and bass, to the most general, harmonizing a chorale.

ANNs offer an alternative for algorithmic composition to the traditional symbolic AI methods, one which loosely resembles the activities in the human brain, but currently they are not as efficient or as practical, at least as a stand-alone approach.

Since composition is a much more highly intellectual process (more "symbolic"), ANNs are capable of successfully capturing the surface structure of a melodic passage and produce new melodies on the basis of the thus acquired knowledge, they mostly fail to pick up the higher-level features of music, such as those related to phrasing or tonal functions" (Toiviainen, 1999).

The other major set of challenges deals with the evaluation of music generated by AI.

The evaluation of creative systems can be categorized into function and structure evaluation, which relates directly to the summative and formative approaches. While the former aims to assess whether the results of a system meet the stated goal of creativity, the latter focuses on monitoring how the instructional goals and objectives are being met (Colton et al., 2001; Guyot, 1978; Ritchie, 2007). Without a clear definition and consensus on the essence of (human) creativity, summative evaluation remains largely problematic (Jordanous, 2012). As the ultimate judge of creative output is the human (listener or viewer), subjective evaluation is generally preferable in generative modeling.

Objective evaluation in music generation remains another challenge. Given the advantages over subjective evaluation with respect to reproducibility and required resources, several recent studies have assessed their models objectively. We categorize the objective evaluation methods used by the recent studies on data-driven music generation into the following categories: (i) probabilistic measures without musical domain knowledge, (ii) task/model specific metrics, and (iii) metrics using general musical domain knowledge Yang & Lerch (2018).

(i) *Probabilistic measures:* The use of evaluation metrics based on probabilistic measures such as likelihood and density estimation has been successfully used in tasks such as image generation and is increasingly used in music-related tasks as well (Dong et al., 2018; Theis et al., 2016). For example, Huang et al. propose a frame-wise evaluation computing the negative log- likelihood between the model output and the ground truth across frames (Huang et al., 2019). Similarly, Johnson considers the note combinations over time steps of the training data as the ground truth and reports the summation of the generated sequence's log-likelihood across notes and time steps (Johnson, 2017). Since the recurrent model used in his study is trained with the goal of maximizing the log-likelihood of each training sequence, the measure is argued to be a meaningful quantitative measure of the performance. The used probabilistic measures provide objective information, yet Theis et al. (2016) observe that "A good performance with respect to one criterion does not necessarily imply a good performance with respect to another criterion" and provide examples of bad samples with very high likelihoods.

(ii) *Model-specific metrics:* As the approaches and models vary greatly between different generative systems, some of the evaluation metrics are correspondingly designed for a specific model or task. Bretan et al. proposed a metric for successfully predicting a music unit from a pool of units in a generative system by evaluating the rank of the target unit (Bretan et al., 2017). Mogren designed metrics informed by statistical measurements of polyphony, scale consistency, repetitions, and tone span to monitor the model's characteristics during its training (Mogren, 2016). Common to these evaluation approaches is the use of domain-specific, custom-designed metrics as opposed to standard metrics. Obviously, the authors realized the problems with using standard metrics (e.g., edit distance of melodies) as musically meaningless and implemented metrics inspired by domain knowledge. The variability and diversity of the proposed metrics, however, leads to comparability issues. The design of non-standard metrics also poses additional dangers, such as evaluating only one aspect of the output, or evaluating with a metric that is part of the system design.

(iii) *Metrics based on domain knowledge*: To address the multi-criteria nature of generative systems and their evaluation (Briot et al., 2019), various humanly interpretable metrics have been proposed. More specifically, these metrics integrate musical domain knowledge and enable detailed evaluation with respect to specific music characteristics. Chuan et al. utilize metrics modeling the tonal tension and interval frequencies to compare how different feature representations can influence a model's performance (Chuan & Herremans, 2018). Sturm et al. provide a statistical analysis of the musical events (occurrence of specific meters and modes, pitch class distributions, etc.), followed by a discussion with examples on the different application scenarios (Sturm & Ben-Tal, 2017). Similarly, Dong et al. apply statistical analysis including tonal distance, rhythmic patterns, and pitch classes to evaluate a multi-track music generator (Dong et al., 2018). The advantages of metrics taking into account domain knowledge are not only in their interpretability, but also in their generalizability and validity — at least as long as the designed model aims to generate music under the established rules.

Brown (2015) affirms a general principle that certain knowledge is better acquired through active participation. Interacting with a system tells you more about its interactive capacity than watching an interaction with a third party (Brown, 2015).

## III. Research Methodology

As mentioned earlier, this study addresses the following research questions:

*RQ1: Is there an awareness about AI-generated music among listeners in the Indian state of Gujarat?*
*RQ2. What are the attitudes of listeners in the Indian state of Gujarat towards music generated by AI?*
*RQ3: Can Indian listeners differentiate between music generated by AI and by humans?*

Considering the wide popularity of music among listeners of all ages, a broad-based electronic questionnaire survey was deemed the most suitable for collection of data. The scope of the study was limited to the state of Gujarat. The sample size for the survey was 150. The research instrument for the surveys was a structured questionnaire with close-ended questions that was administered electronically to music listeners in Gujarat. The questionnaire had four music clippings – two that were generated by AI and two that were composed by humans. The sampling method used was convenience sampling.

## IV. Results

Tables 1 to 4 show the demographic composition of the sample.

***Table 1:*** *Demographic Composition: Age of Respondents*

| **Age** | **Percentage of Respondents** |
|---|---|
| Less than 18 | 15 |
| 18 to 25 | 19 |
| 26 to 35 | 41 |
| 36 to 44 | 17 |
| 45 to 60 | 6 |
| Greater than 60 | 1 |
| **Total** | **100** |

*Table 2: Demographic Composition: Educational Qualifications of Respondents*

| **Educational Qualification** | **Percentage of respondents** |
|---|---|
| High School | 7 |
| 12th Grade | 14 |
| Graduate | 36 |
| Post-Graduate | 32 |
| Professional Degree | 8 |
| PhD | 3 |
| **Total** | **100** |

*Table 3: Demographic Composition: Gender of Respondents*

| Gender | Percentage of respondents |
|---|---|
| Male | 61 |
| Female | 39 |
| **Total** | **100** |

*Table 4: Demographic Composition: Formal Training in Music by Respondents*

| Formal Training in Music | Percentage of Respondents |
|---|---|
| No | 55 |
| Yes | 45 |
| **Total** | **100** |

Majority of the respondents i.e., 41% belong to the age group of 26-35 years while only 1% of the respondents are in the age group of above 60. Major of the respondents i.e., 36% are graduates followed by 32% of the respondents being post-graduates. Only 3% of the respondents have pursed Ph.D. Major of the respondents are males i.e., 61%. Majority of the respondents (55%) haven't or aren't learning music formally while 45% are learning music formally.

*Table 5: Involvement in Music*

| Particulars | Strongly Disagree | Disagree | Neutral | Agree | Strongly Agree | Total |
|---|---|---|---|---|---|---|
| I like listening to music | 3 | 3 | 15 | 23 | 56 | 100 |
| I listen to music sometimes but am not very involved with it | 11 | 17 | 17 | 28 | 26 | 100 |
| I listen to music everyday | 5 | 9 | 21 | 25 | 41 | 100 |
| I am passionate about listening to music | 6 | 10 | 17 | 35 | 31 | 100 |
| I do not like listening to music | 43 | 14 | 14 | 11 | 19 | 100 |
| Record labels should openly/clearly inform if songs or albums were written by AI | 3 | 5 | 30 | 28 | 34 | 100 |
| Music’s value will decrease in society if it is composed by AI | 11 | 14 | 34 | 23 | 18 | 100 |
| AI composed music should be cheaper | 3 | 8 | 38 | 26 | 25 | 100 |
| Professional musicians should not use AI for composing their music | 7 | 16 | 37 | 19 | 21 | 100 |
| I would enjoy music created by AI | 3 | 8 | 29 | 35 | 25 | 100 |
| I would like to purchase music created by AI | 8 | 16 | 29 | 28 | 19 | 100 |
| I would like to download for free music created by AI | 3 | 8 | 25 | 32 | 32 | 100 |
| I would like to stream music created by AI | 4 | 6 | 28 | 34 | 29 | 100 |

Majority of the people surveyed like listening to music. This is shown by the consistent results achieved after repeatedly asking the same question in a different manner always. There was a slight change however, from 56% to 41%, when the question was asked in a negative form.

The listeners mainly swayed over to the positive side when asked questions about Artificial Intelligence in Music. However, in many questions, majority of people have chosen neutral as their answer. This shows that many people still have less knowledge about AI and Music.

From the table above, we learn that majority of people are unsure whether they’ll buy music generated by AI. However, majority of people would stream and download music created by AI, for which they would not have to pay.

*Table 6: Responses after Listening to Music Piece 1: Level of Enjoyment*

| Level of Enjoyment | Percentage of Respondents |
|---|---|
| Really did not enjoy it | 4 |
| Did not enjoy it | 6 |
| Unsure | 16 |

| | |
|---|---|
| Did enjoy it | 74 |
| Really did enjoy it | 0 |
| **Total** | **100** |

The first piece of music in the survey is a song is called *I am AI* and is made by AIVA (Artificial Intelligence Virtual Artist). Majority of the respondents i.e., 74% did enjoy this music piece while 16% were unsure. Only 4% of the respondents really did not enjoy the music piece. Majority of people, about 3/4th of them, gave positive comments about this piece of music.

*Table 7: Opinions after Listening to Music Piece 1*

| | Percentage of respondents | | | | | |
|---|---|---|---|---|---|---|
| **Particulars** | **Strongly Disagree** | **Disagree** | **Neutral** | **Agree** | **Strongly Agree** | **Grand Total** |
| I enjoyed this performance | 4 | 8 | 21 | 34 | 33 | 100 |
| The performance was expressive | 5 | 9 | 24 | 34 | 28 | 100 |
| The execution of the performance was good (well played) | 4 | 10 | 24 | 30 | 32 | 100 |
| This piece was composed by a human | 6 | 8 | 31 | 30 | 25 | 100 |
| This piece was composed by a non-human (robot or computer generated) | 14 | 21 | 23 | 25 | 17 | 100 |
| I would recommend this piece of music to someone | 6 | 10 | 21 | 32 | 31 | 100 |

Majority of the people agree that this performance was expressive (34%) and enjoyable (34%). Majority of people strongly agree that this piece was well played. When asked whether this piece was made by human, 31% respondents were neutral, while 55% agreed that it was produced by a human. On the other hand, when asked if this piece was composed by a robot, 42% respondents believed that this was made by a robot. Thus, 42% respondents could correctly identify the source of this music.
Majority of people (63%) agree that they will recommend this piece to someone.

*Table 8: Responses after Listening to Music Piece 2: Level of Enjoyment*

| **Level of Enjoyment** | **Percentage of Respondents** |
|---|---|
| Really did not enjoy it | 1 |
| Did not enjoy it | 6 |
| Unsure | 26 |
| Did enjoy it | 45 |
| Really did enjoy it | 21 |
| **Total** | **100** |

Piece 2 in the questionnaire is a song called *Strobe* and is composed by the musician deadmau5. Majority of the respondents i.e., 45% enjoyed the music piece while only 1% did really enjoy the music piece. 26% of the respondents were unsure of it. Majority of people, about 3/4th of them, gave positive comments about this piece of music.

*Table 9: Opinions after Listening to Music Piece 2*

| | Percentage of respondents | | | | | |
|---|---|---|---|---|---|---|
| **Particulars** | **Strongly Disagree** | **Disagree** | **Neutral** | **Agree** | **Strongly Agree** | **Total** |
| I enjoyed this performance | 3 | 10 | 22 | 35 | 30 | 100 |
| The performance was expressive | 3 | 12 | 30 | 28 | 26 | 100 |
| The execution of the performance was good (well played) | 3 | 10 | 26 | 34 | 27 | 100 |
| This piece was composed by a human | 5 | 10 | 26 | 30 | 28 | 100 |
| This piece was composed by a non-human (robot or | 8 | 22 | 30 | 23 | 17 | 100 |

| | | | | | | |
|---|---|---|---|---|---|---|
| computer generated) | | | | | | |
| I would recommend this piece of music to someone | 4 | 14 | 22 | 29 | 32 | 100 |

Majority of people agree that they enjoyed this performance (35%) and that this piece was well played (34%). Majority of people (30%) were unsure whether this piece of music was expressive. When asked whether this piece was made by human, 26% respondents were neutral, while 58% agreed that it was produced by a human. On the other hand, when asked if this piece was composed by a robot, 40% respondents believed that this was made by a robot. Thus, 58% respondents could correctly identify the source of this music.
Majority of people (61%) agree that they will recommend this piece to someone.

*Table 10: Responses after Listening to Music Piece 3: Level of Enjoyment*

| Level of Enjoyment | Percentage of Respondents |
|---|---|
| Really did not enjoy it | 3 |
| Did not enjoy it | 3 |
| Unsure | 23 |
| Did enjoy it | 46 |
| Really did enjoy it | 25 |
| **Total** | **100** |

Piece 3 in the questionnaire is a song called *Finale* composed by the music group Polyphia. Majority of the respondents i.e., 46% enjoyed the music piece while only 3% respondents did really enjoy. 23% of the respondents were unsure of it. Majority of people, about 3/4$^{th}$ of them, gave positive comments about this piece of music.

*Table 11: Opinions after Listening to Music Piece 3*

| | Percentage of respondents | | | | | |
|---|---|---|---|---|---|---|
| **Particulars** | **Strongly Disagree** | **Disagree** | **Neutral** | **Agree** | **Strongly Agree** | **Grand Total** |
| I enjoyed this performance | 3 | 7 | 20 | 32 | 37 | 100 |
| The performance was expressive | 4 | 9 | 26 | 28 | 33 | 100 |
| The execution of the performance was good (well played) | 1 | 8 | 26 | 32 | 33 | 100 |
| This piece was composed by a human | 1 | 11 | 28 | 30 | 30 | 100 |
| This piece was composed by a non-human (robot or computer generated) | 12 | 16 | 35 | 19 | 17 | 100 |
| I would recommend this piece of music to someone | 5 | 8 | 22 | 32 | 32 | 100 |

Majority of people strongly agree that they enjoyed this performance (37%), this performance was expressive (33%) and that this piece was well played (33%). When asked whether this piece was made by human, 28% respondents were neutral, while 60% agreed that it was produced by a human. On the other hand, when asked if this piece was composed by a robot, 36% respondents believed that this was made by a robot. Thus, 60% respondents could correctly identify the source of this music.
Majority of people (64%) agree that they will recommend this piece to someone.

*Table 12: Responses after Listening to Music Piece 4: Level of Enjoyment*

| Level of Enjoyment | Percentage of Respondents |
|---|---|
| Really did not enjoy it | 5 |
| Did not enjoy it | 5 |
| Unsure | 14 |
| Did enjoy it | 49 |

| | |
|---|---|
| Really did enjoy it | 26 |
| **Total** | **100** |

The last piece in the questionnaire is a song called *On the edge* and is made by the AI program AIVA. While 49% of the respondents did enjoy the music piece 5% of the respondents did not enjoy the same. 14% of the respondents were unsure of it.

*Table 13: Opinions after Listening to Music Piece 4*

| | Percentage of respondents | | | | | |
|---|---|---|---|---|---|---|
| **Particulars** | **Strongly Disagree** | **Disagree** | **Neutral** | **Agree** | **Strongly Agree** | **Total** |
| I enjoyed this performance | 5 | 8 | 16 | 34 | 38 | 100 |
| The performance was expressive | 5 | 10 | 19 | 35 | 31 | 155 |
| The execution of the performance was good (well played) | 5 | 6 | 22 | 31 | 35 | 100 |
| This piece was composed by a human | 3 | 11 | 29 | 30 | 27 | 100 |
| This piece was composed by a non-human (robot or computer generated) | 10 | 17 | 31 | 21 | 21 | 100 |
| I would recommend this piece of music to someone | 5 | 5 | 23 | 32 | 35 | 100 |

Majority of people strongly agree that they enjoyed this performance (38%) and that this piece was well played (35%). Majority of people (35%) agree that this performance was expressive. When asked whether this piece was made by human, 29% respondents were neutral, while 57% agreed that it was produced by a human. On the other hand, when asked if this piece was composed by a robot, 42% respondents believed that this was made by a robot. Thus, 42% respondents could correctly identify the source of this music.
Majority of people (67%) agree that they will recommend this piece to someone.

***Table 14: Summary of Identification of AI Versus Human Generated Music***

| **Music Piece** | **Correctly Identified** | **Incorrectly Identified** |
|---|---|---|
| 1 | 42% | 35% |
| 2 | 58% | 15% |
| 3 | 60% | 12% |
| 4 | 42% | 27% |
| **Average** | **51%** | **22%** |

The above table shows a summary of the percentage of respondents who correctly or incorrectly identified a piece of music as having been composed by AI or humans. On an average 51% respondents could correctly identify the source of the music, while 22% could not do so. The remaining 27% were neutral in their opinion about the origin of the music.

## V. Discussion

This study found that the attitude of music listeners in India towards music generated by AI ranges from neutral to positive, indicating a moderately favorable attitude. The most positive attitude is found towards free downloading and streaming of music generated by AI while the least positive is towards purchasing AI-generated music.

There is a clear expectation that record labels should openly/clearly inform if songs or albums were written by AI and that AI composed music should be cheaper. Listeners in India also believe that music's value will decrease in society if it is composed by AI and that Professional musicians should not use AI for composing their music.

In terms of distinguishing between music created by AI and humans, preferences, in each piece of music given to the listeners, 51percent respondents were able to clearly identify whether it was created by AI or by humans.

A high percentage of respondents were willing to recommend AI generated music to their friends.

*Limitations*

The study has some limitations. Since the sample size is small, the results may not be generalized to a larger population. Additionally, the respondents were from the state of Gujarat in India, and their views may not be the same as those of music listeners in other Indian cities. There may be a bias related to the sampling method. The sample was non-random where music listeners were approached on a convenience basis. It is possible that listeners of certain types of music would be more positive in their responses about AI-generated music.

*Scope for Future Research*

Future research could compare the preferences of music lovers for AI-generated and human generated music across various genres of music. It would also be interesting to compare the preferences of music listeners for AI-generated music across various states in India.

*Implications*

The findings of this study make several contributions to the existing literature on AI-generated music. First, it offers insight into the level of awareness about AI-generated music, the attitudes of Indian listeners towards such music and their preferences for purchasing, downloading or streaming such music. Secondly, this study also shows whether regular music listeners are able to distinguish between AI and human generated music.

In terms of practical implications, the findings of this study can help creators of AI-generated music understand the importance of creating awareness about such music. It will also help them in developing strategies for encouraging purchase, download and streaming of AI-generated music. This is especially important for India which has a large population that has been listening to music over traditional forms such as the radio, and is now migrating to electronic mediums of listening to music.

## VI. Conclusion

This quantitative study investigates the level of awareness about AI generated music among Indian listeners. It examines the willingness of Indian music listeners to purchase, download, stream or recommend AI generated music. It also demonstrates that more than half of music listeners are able to distinguish between music generated by AI and humans. It fills the gap in the existing research on use of AI-generated music in India and provides valuable insights to developers of such music.

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